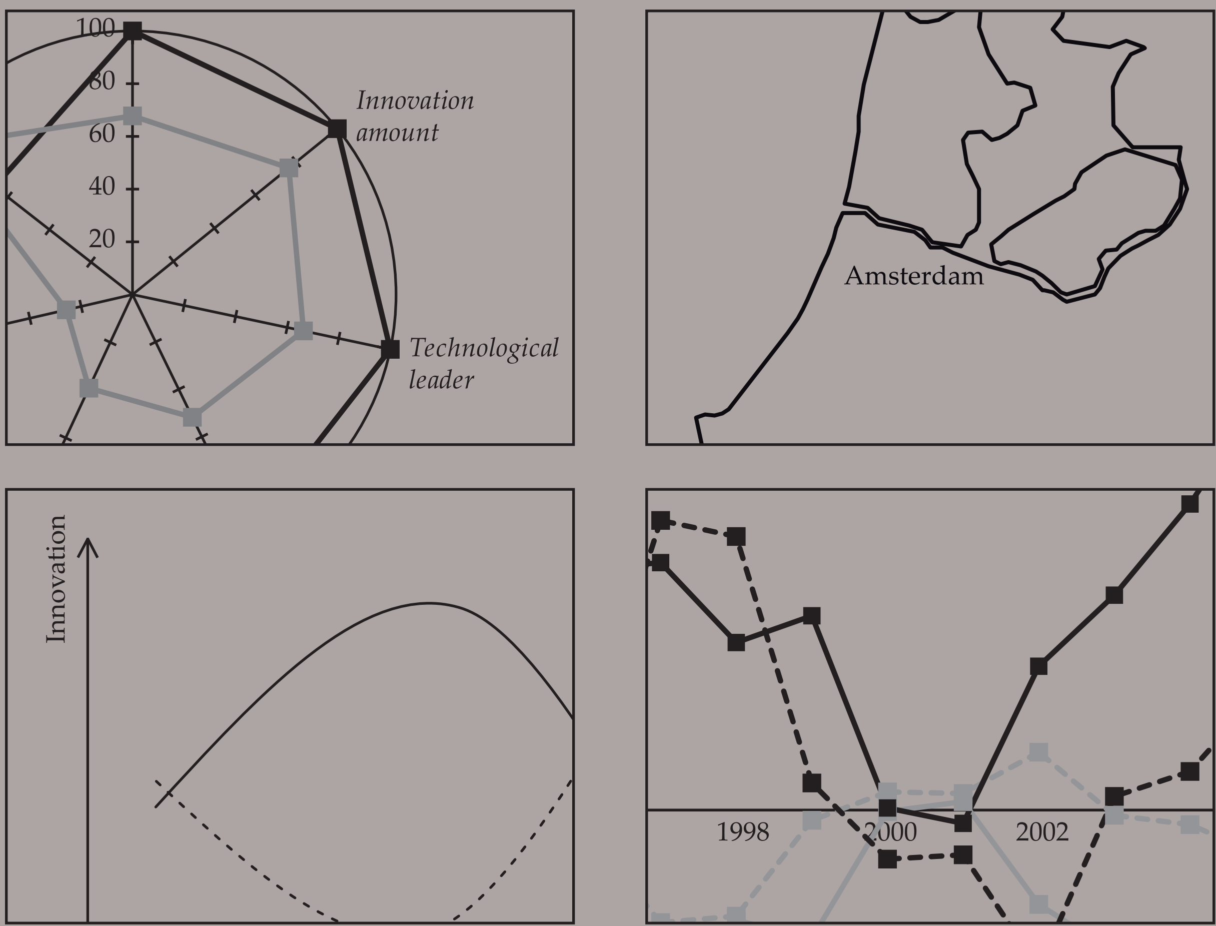
Five Essays on the Interaction between Innovation and the Labor Market



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Five Essays on the Interaction between Innovation and the Labor Market

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Publication and Submission Record

The results of the first essay, Wage bargaining and process innovation, were presented at the Barcelona Graduate School of Economics (GSE) Summer School *Dynamic Panel Data Models and non-linear Panel Data Models* in 2010 in Barcelona, Spain. The essay was presented at the poster session of the conference *Increasing Labor Market Flexibility - Boon or Bane?* organized by the Institute for Employment Research (IAB) and the Labor and Socio-Economic Research Center at the University Erlangen-Nuremberg (LASER), in Nuremberg, Germany in 2011. In addition, it was invited in 2011 to the *2nd Workshop Industrial Organization: Theory, Empirics and Experiments* of the University of Salento in Lecce, Italy. The essay is under review by the Cambridge Journal of Economics (submission date April 16, 2012).

The results of the second essay, Wage bargaining and product innovation, were presented at the Barcelona GSE Summer School *Dynamic Panel Data Models and non-linear Panel Data Models* in 2010 in Barcelona, Spain. The essay was presented in 2011 at the seminar series of the Amsterdam Institute for Advanced Labour Studies (AIAS) in Amsterdam, the Netherlands, and at the *29th International Labour Process Conference* in Leeds, England. In addition, it was invited to the *4th User Conference* of the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the IAB in Nuremberg, Germany. The essay is currently under review by the *Journal for Labour Market Research* (submission date April 5, 2012).

The essay entitled More flexibility for more innovation? was presented in 2011 at the workshop of the Intellectual Property Research Institute of Australia (IPRIA) at the Melbourne Institute in Melbourne, Australia. In addition, it is accepted for presentation and publication in the conference proceedings by the commitee of the *41th Australian Conference of Economists (ACE)* 2012 in Melbourne, Australia, with the theme of The Future of Economics: Research, Policy and Relevance. The working paper version is published in 2012 in the Working Paper Series of the AIAS in Amsterdam, the Netherlands (WP#115). The essay has been submitted to *Industrial and Corporate Change* (submission date April 17, 2012).

The fourth essay, Innovative human resource management, was reviewed by the committee of the International Labour and Employment Relations Association (ILERA) and will be presented at the *2012 Meeting of the HRM* Stu*dy Group of the ILERA* at the *16th World Congress* in Philadelphia, United States. The essay will be published in the IIRA HRM Study Group Working Papers in Human Resource Management Series and is intended to be published in a special issue on *HRM and Social Innovation* of the *International Studies of Management and Organization* journal. In addition, it is invited to the *14th International Schumpeter Society Conference (ISS)* in 2012 in Brisbane, Australia, and the *7th Annual London Business Research Conference* in London, England.

The last essay, Skill-biased labor demand, was presented in 2012 at the workshop of the IPRIA at the Melbourne Institute in Melbourne, Australia. In addition, it is reviewed and accepted by the committee of the *IX International Colloquium Inequality and its Persistence* in 2012 in Graz, Austria, as well as of the *11th International Conference of the Japan Economic Policy Association 2012* in Nagoya, Japan. The essay is currently under review by the commitee of the Workshop on *Labor Market Search and the Business Cycle* in 2012 in Konstanz, Germany.

Summary

This thesis deals with the interaction between innovation activities and aspects of the labor market. Innovation is considered to be a driving force for productivity, competitiveness and growth. The development of innovations is understood as a complex process that is influenced by various actors from a technical and a social point of view. In this way, the regional, national and international environment, including its political frameworks and specific economic structures, affect the generation of innovations. The environment also includes the supply of labor and knowledge and the efficient use of available human capital resources. At the same time, the economic and social context is not fixed. Demographic change, globalization and the associated increasing international competition causes economic and social changes and requires greater adaptability and mobility of companies and employees. To keep unemployment low and to ensure an efficient labor market, the institutions of the labor market must adapt to more flexible requirements. Many labor market economists have indeed argued in favor of greater labor market flexibility, especially after the sharp rise in unemployment in Europe in the 1970s and 1980s. Given the recent financial crisis and its impact on the economic context, the issue of labor market flexibility has become more important again.

This thesis is devoted to understand the interactions between innovation and labor market characteristics. In five essays, several aspects of interaction at the European and non-European level are highlighted. The first two essays deal primarily with financial labor market flexibility, while the third essay expands the analysis to further aspects of labor market flexibility. The fourth essay considers the management of corporate human capital resources in terms of innovation activities. Finally, the fifth essay analyzes a reverse direction of effect in terms of potential repercussions of technological changes on the labor market.

The first essay, Wage bargaining and process innovation, examines the relationship between collective wage-setting and process innovations. Three wage-setting processes are considered: the decentralized bargaining for individual companies, centralized bargaining at industry level and coordinated wage-setting at company level. According to a theoretical model, bargaining at industry level offers the highest incentive to invest in cost-reducing process innovations. In contrast, the incentive is lowest when wages are set at the company level. Hence, the relationship between the centralization of wage bargaining and the incentive to innovate is not linear. Using data from German establishments from 1996 to 2008, the assumed non-linearity cannot be found. Moreover, union wage bargaining continuously decreases the probability of process innovations. In addition, the existence of works councils is negatively associated with new process developments. Despite the decreasing number of union members in Germany, works councils are still regarded as an important mediator between unions and companies. They have no incentive to support a labor-saving process innovation, especially if it is not an incremental process innovation.

Based on these results, the second essay, Wage bargaining and product innovation, addresses the question of whether the predictions of the theoretical model used in the first essay are transferable to product innovations. Using an advanced theoretical model, related hypotheses are derived, which are tested empirically with the same dataset. The results also disprove the hypothesis of a non-linear relationship between wage-setting levels and innovation incentives. The probability of a product innovation is always lower when wages are negotiated collectively. However, the

negative correlation is mitigated by the existence of works councils, who have an incentive to support a job-creating product innovation. This does not apply to radical product innovations that are associated with higher previous investments and correspondingly, an increased risk for the company and its employees.

The third essay, More flexibility for more innovation?, further elaborates on the topic of labor market flexibility. In addition to financial aspects, labor market flexibility is measured by the number of part-time employees as well as flexible and temporary working contracts. A comprehensive analysis of labor market flexibility and its impact on innovation is carried out based on a Dutch employer-employee level dataset from 1998 to 2008. Separate regression calculations for process and product innovations show a significant correlation, which in turn depends on the measurement of labor market flexibility and the type of innovation. It turns out that process innovations require an increased financial flexibility, while product innovations, in contrast, depend much more on incentives such as higher labor security.

The fourth essay, Innovative human resource management, deals with human resource management (HRM) practices and their impact on a company's innovation activities. The essay uses an Australian dataset from 2001 to 2010, which includes not only information on the innovation efforts, but also on a variety of HRM practices. Using a cluster analysis, four types of companies with increasing degree of innovation activities can be identified: non-innovators, adapters, small innovators and pioneers. The regression results show a consistently positive relationship between HRM practices and innovation, especially for highly innovative pioneers. Aspects of payment and communication present the highest correlation. However, not the mere number of applied HRM practices, but rather the right combination seems to be crucial for the innovation strategy.

The last essay, Skill-biased labor demand, considers potential repercussions of innovation activities on the labor market. According to the economic literature, technological change increases the demand for highly educated workers. Innovations require the use of employees with high education levels and are therefore biased towards higher skills. Several studies have already found evidence for this hypoth-

esis, in particular those using data from the United States and Great Britain. Organizational change as a possible cause of the bias, however, has been given less attention. The analysis of a Western German linked employer-employee level dataset from 1993 to 2008 shows that the increasing demand for highly educated workers can be attributed not only to technological, but also to organizational changes, especially in manufacturing sectors.

In summary, this thesis provides evidence of a strong correlation between different aspects of the labor market and the innovation behavior of companies. On the one hand, there is a relationship between the labor market and its institutions as well as the use of available human capital resources and innovation activities. It shows in particular that an increased communication and participation of both parties can create innovation incentives. On the other hand, the thesis shows that innovations can influence and change the labor market. Technological and organizational changes lead to an increased demand for educated workers, which results in requirements for the national education system as well as for internal training practices within the companies. Future research might focus on the efficiency of such practices in order to face the increasing skill demand. Given the current changes on the labor markets, the detailed role of individual participants in the innovation process, such as works councils or employees with a flexible working contract, should be analyzed. In addition, the nature of effect of innovation and labor market characteristics should be given more attention, which also requires comprehensive datasets as well as qualitative research.

Zusammenfassung

Diese Arbeit befasst sich mit den Wechselwirkungen von Innovationsaktivitäten und Aspekten des Arbeitsmarktes. Innovation gilt als treibende Kraft für Produktivität, Wettbewerbsfähigkeit und Wachstum. Die Entstehung einer Innovation wird als komplexer Prozess verstanden, der von verschiedenen Akteuren in technischer und sozialer Hinsicht beeinflusst wird. Auf diese Weise wirkt sich das regionale, nationale und auch internationale Umfeld, einschließlich seiner politischen Rahmenbedingungen und spezifischen Wirtschaftsstruktur auf die Generierung von Innovationen aus. Dazu zählen ebenso auch die Versorgung mit Arbeitskräften und Wissen sowie der effiziente Einsatz vorliegender Humankapitalpotenziale. Zugleich führen der demografische Wandel, die Globalisierung und der damit verbundene zunehmende internationale Wettbewerb sowohl zu wirtschaftlichen als auch zu sozialen Veränderungen, die eine größere Anpassungsfähigkeit und Mobilität von Unternehmen und ihren Mitarbeitern erfordern. Aus diesen Gründen verlangen viele Ökonomen nach einer größeren Flexibilität auf den Arbeitsmärkten, insbesondere nach dem starken Anstieg der Arbeitslosigkeit in Europa in den 1970er und 1980er Jahren. Angesichts der aktuellen Finanzkrise und deren wirtschaftliche Auswirkungen, gewinnt das Thema der Arbeitsmarktflexibilität erneut an Bedeutung.

Die vorliegende Dissertation widmet sich dem Verständnis des Zusammenspiels beider Themengebiete. In insgesamt fünf Essays werden verschiedene Interaktionsaspekte sowohl auf europäischer als auch auf außereuropäischer Ebene beleuchtet. Die ersten beiden Essays widmen sich insbesondere der finanziellen Arbeitsmarktflexibilität, während im dritten Essay ein Ausbau auf weitere Aspekte der Arbeitsmarktflexibilität erfolgt. Im vierten Essay wird das Management der Humankapitalressourcen innerhalb von Unternehmen im Hinblick auf Innovationsaktivitäten betrachtet. Abschließend wird im fünften Essay eine umgekehrte Wirkungsrichtung in Form möglicher Rückwirkungen technologischer Veränderungen auf den Arbeitsmarkt analysiert.

Das erste Essay, Wage Bargaining and Process innovation, untersucht den Zusammenhang zwischen kollektiver Lohnsetzung und Prozessinnovationen. Neben dezentralen Verhandlungen für einzelne Unternehmen wird zwischen Verhandlungen auf Branchen- und Firmenebene unterschieden. Einem theoretischen Modell zufolge lassen sich die höchsten Anreize zur Einführung einer Prozessinnovation bei Verhandlungen auf Branchenebene finden, während die Anreize bei einer Lohnsetzung auf Firmenebene am geringsten sind. Anhand von Daten deutscher Betriebe in den Jahren von 1996 bis 2008 lässt sich die unterstellte Nicht-Linearität zwischen der Zentralisation der Lohnsetzung und den Innovationsanreizen jedoch nicht feststellen. Vielmehr wird die Wahrscheinlichkeit einer Prozessinnovation durch jegliche gewerkschaftliche Lohnverhandlung verringert. Die Existenz von Betriebsräten ist zusätzlich negativ mit Prozessinnovationen korreliert. Betriebsräte gelten trotz der abnehmenden Anzahl an Gewerkschaftsmitgliedern in Deutschland weiterhin als einflussreicher Vermittler zwischen Gewerkschaften und Unternehmen. Sie haben keinen Anreiz, eine meist arbeitsplatzsparende Prozessinnovation zu unterstützen, insbesondere wenn es sich nicht um eine inkrementelle Prozessinnovation handelt.

Aufbauend darauf widmet sich das zweite Essay, Wage bargaining and product innovation, der Frage, inwiefern die theoretischen Annahmen des ersten Essays auf Produktinnovationen übertragbar sind. Mit Hilfe einer erweiterten theoretischen Basis können analoge Hypothesen abgeleitet werden, die anhand der gleichen Datenbasis empirisch getestet werden. Die Ergebnisse widerlegen ebenfalls die Hypothese eines nicht-linearen Zusammenhangs zwischen der Lohnsetzungsebene und Innovationsanreizen. Die Wahrscheinlichkeit einer Produktinnovation ist bei gewerkschaftlicher Lohnsetzung immer geringer. Dieser Einfluss wird jedoch durch die Existenz von Betriebsräten etwas aufgefangen, die einen Anreiz haben, eine meist arbeitsplatzschaffende Produktinnovation zu unterstützen. Dies gilt jedoch nicht für eine drastische Produktinnovation, die mit einem höheren Investitionsaufwand und einem dementsprechend steigenden Risiko für ein Unternehmen und seine Mitarbeiter verbunden ist.

Das dritte Essay, More flexibility for more innovation?, weitet das Thema der Arbeitsmarktflexibilität weiter aus. Zusätzlich zu finanziellen Aspekten wird Arbeitsmarktflexibilität mit Hilfe der Anzahl von Teilzeitbeschäftigten sowie flexiblen und befristeten Arbeitsverträgen gemessen. Eine empirische Analyse erfolgt anhand von niederländischen Daten der Jahre 1998 bis 2008, die Informationen sowohl auf Beschäftigten- als auch auf Unternehmensebene zusammenbringen. Getrennte Regressionsrechnungen für Prozess- und Produktinnovationen zeigen einen signifikanten Zusammenhang, der nicht nur von der Messung der Arbeitsmarktflexibilität, sondern auch von der Art der betrachteten Innovation abhängt. Es zeigt sich, dass Prozessinnovationen eine größere finanzielle Flexibilität erfordern, während Produktinnovationen im Gegensatz dazu viel stärker von Anreizen wie etwa der Sicherheit des Arbeitsplatzes abhängen.

Das vierte Essay, Innovative human resource management, befasst sich mit Human Ressource Management (HRM) Praktiken und deren Einfluss auf die Innovationsaktivitäten eines Unternehmens. Das Essay verwendet einen australischen Datensatz der Jahre 2001 bis 2010, der nicht nur Angaben zum Innovationsbemühen, sondern auch zu einer Vielzahl an HRM Praktiken beinhaltet. Mit Hilfe einer Clusteranalyse können vier Typen an Unternehmen mit zunehmendem Grad an Innovationstätigkeiten ausgemacht werden: Nicht-Innovatoren, Adaptoren, Kleine Innovatoren und Pioniere. Die Regressionsergebnisse zeigen einen durchgehend positiven Zusammenhang zwischen HRM Praktiken und Innovation, insbesondere für die als hochinnovativ geltenden Pioniere. Aspekte der Bezahlung und der Kommunikation zeigen insgesamt die stärkste Korrelation. Dabei ist jedoch nicht die reine Anzahl an angewandten HRM Praktiken entscheidend, sondern vielmehr die richtige inhaltliche Abstimmung je nach Innovationsstrategie.

Das letzte Essay, Skill-biased labor demand, betrachtet eine umgekehrte Wirkungsrichtung im Hinblick auf Arbeitsmarkt und Innovation. Entsprechend der ökonomischen Literatur sind technologische Veränderungen für eine steigende Nachfrage nach hochgebildeten Arbeitskräften verantwortlich. Innovationen, die den Einsatz von Mitarbeitern mit hohem Bildungsniveau voraussetzen, sind demzufolge verzerrt in Richtung höherer Fähigkeiten. Bereits mehrere Studien konnte diese These insbesondere für Daten aus den Vereinigten Staaten und Großbritannien belegen. Organisatorische Veränderungen als mögliche Ursache für die Verzerrung wurden bisher jedoch weniger berücksichtigt. Die Analyse eines Datensatzes auf Betriebs- und Personenebene in Westdeutschland von 1993 bis 2008 zeigt, dass die steigende Nachfrage nach Hochgebildeten in Dienstleistungen auf technologische, in Industriesektoren jedoch mehr auf organisatorische Veränderungen zurückgeführt werden kann.

Zusammenfassend liefert die vorliegende Dissertation deutliche Hinweise auf eine enge Verbindung zwischen Aspekten des Arbeitsmarktes und dem Innovationsverhalten von Unternehmen. Zum einen besteht ein Zusammenhang zwischen Arbeitsmarktinstitutionen sowie der Verwendung der zur Verfügung stehenden Humankapitalressourcen und Innovationsaktivitäten. Dabei zeigt sich insbesondere, dass eine verstärkte Kommunikation und Partizipation beider Parteien Innovationsanreize schaffen kann. Auf der anderen Seite zeigt die Dissertation, dass auch Innovationen den Arbeitsmarkt beeinflussen und verändern können. Technologische und auch organisatorische Veränderungen führen zu einer erhöhten Nachfrage nach gebildeten Arbeitskräften, aus der sich nicht nur Implikationen für das nationale Bildungssystem ergeben, sondern auch Anforderungen an interne Schulungsmaßnahmen eines Unternehmens abgeleitet werden können. Zukünftige Forschung könnte sich auf die Effizienz von solchen Praktiken beziehen, um der steigenden Qualifikationsnachfrage gerecht zu werden. Angesichts der derzeitigen Veränderungen auf den Arbeitsmärkten sollte zudem die genaue Rolle einzelner Teilnehmer am Innovationsprozess analysiert werden, wie etwa die Partizipation von Betriebsräten oder

Beschäftigten mit flexiblen Arbeitsverträgen. Darüber hinaus verdient die Analyse der Wirkungsrichtung zwischen Innovation und Arbeitsmarktcharakteristika mehr Aufmerksamkeit, wodurch nicht nur die Notwendigkeit des Vorliegens von umfangreichen Datensätzen sowohl auf Arbeitgeber- als auch auf Arbeitnehmerseite, sondern auch der Einsatz von qualitativer Forschung verdeutlicht wird.

Contents

1 Wage bargaining and process innovation
Evidence from Germany

The content of this paper is the relationship between collective wage bargaining levels and process innovations using German establishment data from 1996 to 2008. The question of how unions affect innovation has already been discussed several times. In most cases, a negative relationship is assumed. However, the individual bargaining levels have yet been neglected. In this paper, we analyze whether there is also a consistently negative association and whether it is true that in fact the largest wage flexibility guarantees the largest innovation incentives. We distinguish between three levels of wage bargaining with increasing degree of centralization: decentralized wage-setting for individual companies, bargaining at company and at industry level. Following a theoretical framework, the relationship between the centralization of wage bargaining and process innovation is U-shaped. However, our results cannot prove the assumed non-linearity and show a consistently negative correlation. In addition, process innovations are negatively associated with the existence of works councils, who have no incentive to support a labor-saving innovation, especially if it is not an incremental process innovation.

1.1 Introduction

Trade unions are considered as one of the most important labor market institutions. How they affect the behavior and in particular the profits of a company has been a controversial topic for a long time. Following Freeman and Medoff (1979, 1984), unions have two main effects with different directions. On the one hand, unions have market power, which allows them to increase the wages of their members and provide potential distortions. On the other hand, unions form a necessary representation of the employees in order to prevent inequalities. This so-called collective voice may improve the relationship between employee and employer and result in an increased productivity (Freeman and Medoff, 1979, 1984).

Several empirical studies, analyzing the impact of unionism on profits, show that the negative effects of unionism mostly outweigh the positive effects. According to the analyses of e.g. Freeman (1983), Karier (1985) or Voos and Mishel (1986), unions reduce profits and returns from investments, especially in concentrated industries.[1] Following Hirsch and Connolly (1987), union rent-seeking concerns especially investments in intangible assets such as research expenditures. Therefore, the interest of possible influences on investments in knowledge and innovation has been increasing since the late years of the 1980s. The assumed negative relationship between unionism and R&D expenditures can mostly be confirmed, especially for data from the United States (US) (Menezes-Filho and Van Reenen, 2003: 328).

This paper analyzes whether the assumed negative relationship applies to all levels of collective bargaining and if it is true that the largest wage flexibility guarantees the largest innovation incentives. As stated by Hirsch and Link (1987), the bargaining between a company and the union is crucial. An efficient bargaining could prevent any influences on the investment behavior of a company. However, the wage bargaining levels as an indicator for union power have yet been neglected. In addition, we try to determine whether the negative impact can be transferred to all types of innovation, by using a more directly measured innovation variable. Following

[1] Similar studies have been made by e.g. Salinger (1984) or Ruback and Zimmerman (1984). See Freeman and Medoff (1979) or Hirsch and Addison (1986) for a review.

Hirsch and Link (1987: 325), a union may even increase the investment incentives in the case of highly labor-saving process innovations. However, it is not clear whether this applies to all bargaining level. Considering process innovations, our results show a continuously negative association.

The rest of this paper is structured as follows. Chapter 1.2 summarizes the theoretical approaches about the relationship between unionism and innovation. The following Chapter 1.3 gives a literature review of previous empirical studies. Chapter 1.4 represents the underlying theoretical model. The data and the empirical model are discussed in Chapter 1.5 and 1.6, respectively. The results are included in Chapter 1.7. Finally, Chapter 1.8 gives some conclusions.

1.2 Unionism and innovation

Following the theoretical approaches, the relationship between unionism and innovation is not unambiguous.[2] Historically, mostly a negative correlation between unionism and innovation is assumed. Unions are still connected with the events at the beginning of the 19th century. During that time, workers destroyed newly developed machinery mills because they were afraid of being replaced by them. Based on the history, unions could be considered as a blocker of technological change (Menezes-Filho and Van Reenen, 2003: 294-295).[3] However, direct effects may also be positively associated with innovation. The collective voice, as stated by Freeman and Medoff (1979, 1984), can lead to an increase of moral, motivation or training, and therefore help to adapt new technologies.

The most frequently discussed mechanism is the union rent-seeking approach. It is based on the hold-up effect, developed in the model of Grout (1984) and the considerations of Simons (1944). Following Grout, unions capture parts of the investment returns by increasing the wages after the investment. The anticipation of the so-called hold-up situation typically reduces the investment incentives. As stated by

[2] A summary of the theoretical approaches is given by Menezes-Filho and Van Reenen (2003).

[3] The movement is also called Luddite, which occurred especially in the United Kingdom (UK). Examples are the destruction of printing presses or of wool and cotton mills. More information can be found in e.g. Berg (1988) or Horn (2005).

Hirsch and Link (1987) and Connolly et al. (1986), particularly investments in intangible capital such as research and development (R&D) are affected due to the high share of sunk costs that are typically associated with investments in R&D (Menezes-Filho and Van Reenen, 2003: 296). In addition, R&D investments are particularly affected by a possible rent-seeking if the following innovation cannot be licensed or patented, which cannot be assessed in most of all cases before the investment (Connolly et al., 1986: 569). Anticipating the rent-seeking of a union may reduce the innovation incentives and lead to an underinvestment in R&D. However, the negative hold-up effect can also be reduced. According to Ulph and Ulph (1998), the problem could be avoided by long-term and cooperative bargaining contracts, particularly in agreements on wages and employment. In addition, the negotiations between unions and companies take place repeatedly. As stated by Van der Ploeg (1987), unions could lose their reputation as a consequence of rent-seeking. Thus, the willingness of both parties to cooperate could be improved.

In addition to the hold-up effect, two other effects are discussed. As stated by Menezes-Filho and Van Reenen (2003), a strategic R&D effect can occur depending on the market situation. It is based on the fact that companies hope to undertake a competitive advantage through R&D. Following Lingens (2009), unionism can even increase this effect, due to the inferior position of the non-innovating company after collective bargaining. Finally, Lingens (2009) establishes the so-called Arrow effect, which can be observed during the development of an innovation. Union wage bargaining decreases the profits of the companies during the research time. According to the Arrow effect, unionism increases the incentives to invest in R&D in order to minimize the research time. However, the hold-up effect dominates in the model of Lingens, so that collective bargaining always reduces the innovation incentives (Lingens, 2009: 260).

According to the theory, arguments for either a positive or a negative relationship between unionism and innovation can be found. Which effect ultimately dominates is an empirical question.

1.3 Literature review

The presented theories have already been empirically tested several times. Most of all studies use the rent-seeking model, which assumes a negative relationship between unionism and innovation. Previous studies can be distinguished by the type of the dependent variable as well as the measurement of unionism. In most of all cases, the research expenditures are used as dependent innovation variable. A survey of previous studies can be found in Menezes-Filho and Van Reenen (2003: 310-325) and Schnabel and Wagner (1994: 492). A summary of studies on the macroeconomic impact of unionism and collective bargaining is given by Flanagan (1999) or Aidt and Tzannatos (2008).

Connolly et al. (1986) present one of the first empirical studies on unionism and innovation using data from the US. Their empirical models show significantly lower R&D investments in sectors with high union density. Similar negative results with US data are found by Audretsch and Schulenburg (1990), Hirsch (1991, 1992) or Bronars and Deere (1993). The results of Betts et al. (2001) show an even higher negative correlation in several Canadian industries.

The results of studies with European data are more ambiguous. Menezes-Filho and Van Reenen (1998) also present a negative correlation between union density and R&D intensity using data from the UK. However, the significance level decreases after controlling for the company's age as well as technological differences between the industries. Compared to US studies, the R&D intensity seems to be higher in industries with a small union density than in those without a union presence. Using German data, Schnabel and Wagner (1994) does not find any significant association of union density at industry level. A works council is even positively correlated at establishment level if the union density is not too high. Ulph and Ulph (1998) find different results depending on the timing and the content of the agreements. Ex-ante bargaining can be either negatively or positively correlated, while ex-post bargaining mostly has a negative association.

The results of studies relating to the development of process innovations or the adoption of new technologies are ambiguous as well. Drago and Wooden (1994) find a significantly negative association between unionism and the probability to adopt new technologies using Australian establishment data. Keefe (1991) analyzes the relationship between unionism and the use of several new technologies. It turns out that establishments, in which the majority of the employees is affected by collective bargaining, have a lower probability to use specific new technologies such as computer assisted designs. Following Machin and Wadhwani (1991), in contrast, unionism and the adoption of new technology is positively correlated for British establishments. However, the results are not significant anymore after controlling for the existence of consultative committees that can be interpreted as the collective voice as stated by Freeman and Medoff (1979, 1984).

Altogether, most of the studies from the US find negative correlations, while the results of European countries are not as clear (Menezes-Filho and Van Reenen, 2003: 311-312). As stated by Schnabel and Wagner (1992: 370) or Menezes-Filho and Van Reenen (2003: 295), this can be attributed to stronger differences in union structure mechanisms in Europe and the more productivity-enhancing attitude of trade unions in parts of Europe in contrast to the US. The negative rent-seeking approach is based on an inefficient bargaining relationship between unions and companies. Following Schnabel and Wagner (1992), a more cooperative relationship, such as in Germany, may lead to more efficient negotiations and innovation-friendly framework conditions. For example, the existence of works councils can be considered as an opportunity for the advanced communication between employers and employees (Schnabel and Wagner, 1992: 370).[4] In the long run, companies as well as unions benefit from innovations. However, as stated by Schnabel and Wagner (1992), this may also depend on the type of innovation. The incentives for product innovations, that are considered to be job-creating, are likely to be higher than for cost-saving process innovations. It appears that the relationship between unionism and innovation also depends on other aspects such as the bargaining structure. Thereby, it remains unanswered whether the assumed negative correlation applies to all levels of wage bargaining.

[4] More detailed information can be found in Schnabel (1991).

1.4 Theoretical model

The theoretical model of Haucap and Wey (2004) establishes the relationship between different wage bargaining levels and innovation incentives. Three levels of bargaining centralization ρ can be distinguished. Decentralized wage-setting D is defined as wage negotiations between a company and an individual union.[5] It represents the minimum level of centralization. At the coordinated level C, a trade union negotiates on behalf of all employees of a single company. Thus, the union coordinates the employee's wage demands according to the labor productivity of the company. The third level is presented by centralized wage-setting U. In this case, a union determines uniform wages for all employees of an industry.

The model examines a Cournot market for a homogenous good with two competitive companies and constant returns to scale. Labor constitutes the only production factor. A patent race establishes which of the two companies executes the innovation. Only non-radical process innovations are examined, in order to avoid crowding out. That means the decline of the production costs after the innovation is not strong enough to allow monopoly prices. Productivity growth is thus limited to $\Delta \leq 1/3$. Both companies $i = \{1, 2\}$ have a reaction function depending on the quantity of supply q_i, the wages w_i, and the level of productivity Δ

$$q_i(w_i, w_j, \Delta) = \frac{A-2w_i(1-\Delta)+w_j}{3}, \tag{1}$$

with i as the innovating and j as the non-innovating firm. The unions try to maximize the wage demands according to their level of centralization. The utility functions U_i of the unions depend on the level of centralization ρ, the labor demand l_i, resulting from the reaction function in (1), the opportunity costs of the employees w_0 and the wages after the innovation w_i

$$U^D_i = l_i(w_i - w_0), \qquad U^C_i = \sum_{i=1}^{2} l_i(w_i - w_0), \qquad U^U_i = \sum_{i=1}^{2} l_i(w - w_0). \tag{2}$$

According to $w^C_i > w^U_i > w^D_i$, the innovating company pays the highest wages in coordinated wage bargaining and the lowest wages in decentralized negotiations at

[5] The indications correspond to those in the theoretical model of Haucap and Wey (2004).

company level due to the union's reaction to productivity gains. With coordinated wage-setting, the wage level corresponds to the productivity of each firm. An increase of the productivity after an innovation will increase the wage to the same extent. For the non-innovating company, $w^U_j > w^C_j > w^D_j$ holds. It pays the highest wages in centralized wage-setting. Here, the wage is set according to the average industry productivity. After the innovation of the other company, the average productivity increases, which subsequently increases the wages. Due to different productivity levels, the wage differential between the two companies is highest in decentralized wage-setting. In contrast, the industry union ignores productivity differences in centralized wage-setting. In this case, the wages are the same for both companies and the wage differential is $\Delta w^U = 0$.

The level of wage-setting centralization ρ also influences the decision to invest in innovation. A process innovation increases the productivity of a company and creates a competitive advantage. The union, whose wage demands are determined according to the productivity level, benefits from successful innovation. At the same time, the company runs the risk of losing the innovation gains due to equivalent wage increases. This hold-up problem reduces the incentives for investments in innovation. Due to the hold-up problem, the three wage-setting levels ρ have different impacts on the innovation incentives. The problem can most easily be reduced by centralized wage-setting at industry level. In this case, the wages rise to the average productivity of the industry and the innovating firm does not lose all gains from innovation. Employees profit from unified wages as well, although they receive only a part of the innovation gains. Following the results of the theoretical model, three hypotheses can be derived.

Hypothesis I In centralized wage-setting *U*, companies have the highest incentives to invest in process innovations.

Hypothesis II The incentives are lowest in coordinated wage-setting *C*. The relationship between the centralization of wage bargaining and innovation incentives is non-linear.[6]

[6] Similar results are found by Dowrick and Spencer (1994).

The model only applies to incremental process innovations, where the non-innovator is not squeezed out of the market. According to the definitions used in the Oslo Manual of the OECD (2005), incremental innovations, such as process improvements, lead to small cost advantages, while radical innovations reduces the costs more strongly and may even allow to set monopoly prices.

Hypothesis III The first two hypotheses are valid in particular for process innovations, which are classified as incremental.

1.5 Data

The data basis of this paper is the Establishment Panel of the Institute for Employment Research (IABB), wave 1996 – 2008. The data access was carried out by controlled remote data processing at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA).[7] The IABB is a representative survey for all sectors and sizes, collected for Western and Eastern Germany since 1996. The dataset gives information about bargaining levels of around 16,000 establishments. The meaning of the turnover variable in the dataset is not unambiguous. The variable can include the turnover, the total assets, the total premiums paid or the budget volume. Due to deviations in the meaning of turnover, the banking and insurance industry, non-profit as well as public organizations are excluded. All monetary variables are given in Euro (€).

Unfortunately, process innovations are included in the questionnaire only from 2007. The investment in information and communication technology (ICT) serves as an approximation, which is often used as a proxy for process innovation (Möller, 2000: 572; Hempell, 2005: 293). The variable also includes the diffusion of new technologies, which does not differ greatly from the definitions used in other innovation surveys. In the Community Innovation Survey (CIS) of the European Commission, process innovations are defined as new or significantly improved technologies or processes. The degree of novelty is judged by the company itself. Consequently, dif-

7 Further information on the data, the variables and their coding can be found in Städele and Müller (2006).

fusion and imitation of innovation is included.[8] Following the theoretical model, the first two hypotheses only apply to non-radical process innovations. In order to limit the analysis, we use the share of ICT investments in the turnover as a restriction of innovation under the assumption that radical process innovations require higher investments than incremental ones. We consider establishments as incremental process innovators if 30 percent or less of the turnover was invested in ICT.[9]

Table 1.1 summarizes some descriptive statistics of the dataset. 45 percent of all establishments invest in ICT and are considered as process innovators. Thereby, more than 64 percent of the process innovations are incremental. Producer goods and the trade sector as well as technical and other services are the most represented sectors in the dataset. Most of all establishments have less than 50 employees. In contrast, about a quarter of all process innovators have 250 or more employees. More than half of all establishments and even more than 60 percent of the process innovators are located in Western Germany. The share of establishments with their own research department is 15 percent for all companies and 22 percent for process innovators. A works council exists in more than 36 percent of all establishments. However, half of all process innovators and even more than half of all incremental process innovators have a works council. Most of the establishments pay a collectively negotiated wage, although the share is higher for companies with process innovations.

During the observed time period, the share of collectively negotiated wages decreases. Figure 1.1 shows the percentage of establishments with agreements at industry and at company level as well as the percentage of establishments without collective agreements from 1996 to 2008.

8 Following Franklin et al. (2008: 130), there is evidence that investments in ICT as well as the use of ICT can be considered as a proxy for the indicator of process innovations in the CIS survey.

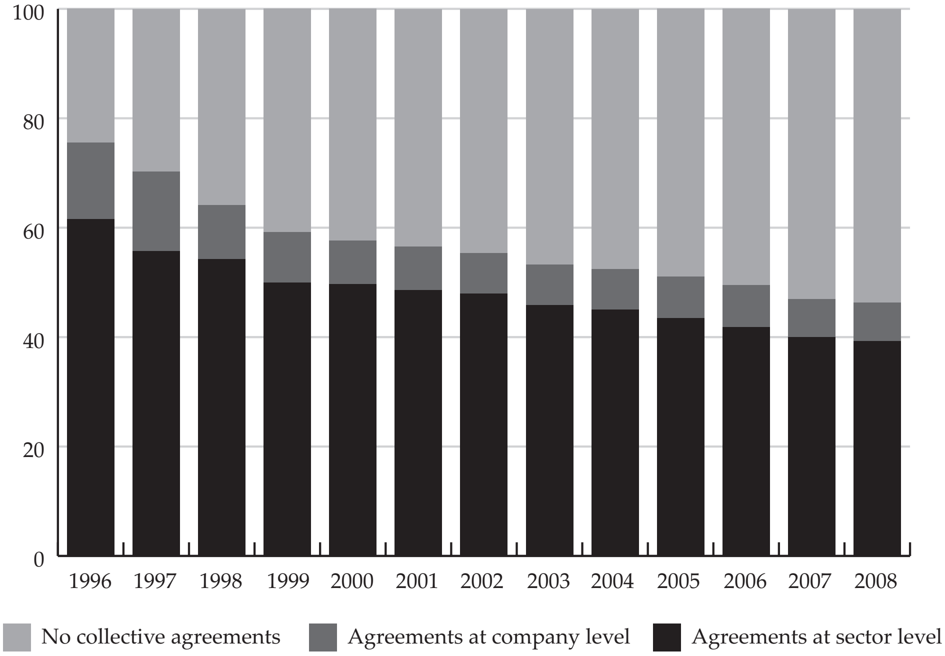
9 It has to noted that the share of investments in ICT is only included from 2000 to 2008 and may be affected by the problem of under-reporting, especially in the case of small-sized establishments.

Table 1.1: Summary of descriptive statistics, percentage.

Descriptive Variables	All companies	Process innovators	Incremental innovators
Process innovation	47.71		
Incremental process innovation	64.28		
Sectors			
Consumer goods	9.27	9.54	7.18
Nutrition	3.1	2.94	4.71
Producer goods	11.05	12.92	23.8
Machine construction	3.52	4.74	7.22
Investment goods	8.09	8.85	7.52
Trade	16.77	14.89	14.58
Transportation	5.38	5.11	5.6
Business services	8.15	10.84	2.5
Technical services	15.57	13.31	8.42
Other services	12.31	9.2	10.63
Real estate	6.79	7.65	7.83
Total	100.00	100.00	100.00
Employment size			
Less than 10	32.68	17.67	12.61
10 to under 25	16.61	14.25	13.09
25 to under 50	12.37	13.19	13.45
50 to under 250	22.32	29.71	34.23
250 and more	16.01	25.18	26.62
Total	100.00	100.00	100.00
Region			
Western Germany	55.98	60.1	63.76
Eastern Germany	44.02	39.9	36.24
Total	100.00	100.00	100.00
R&D department			
No own R&D department	84.61	77.15	74.05
Own R&D department	15.39	22.85	25.95
Total	100.00	100.00	100.00
Employee representation			
No works council	63.86	49.81	45.53
Works council	36.14	50.19	54.47
Total	100.00	100.00	100.00
Collective bargaining			
Agreements at sector level	46.39	52.71	55.15
Agreements at company level	8.26	9.52	9.32
No collective agreements	45.35	37.77	35.53
Total	100.00	100.00	100.00

Source: IABB, 1996-2008. Own calculations.

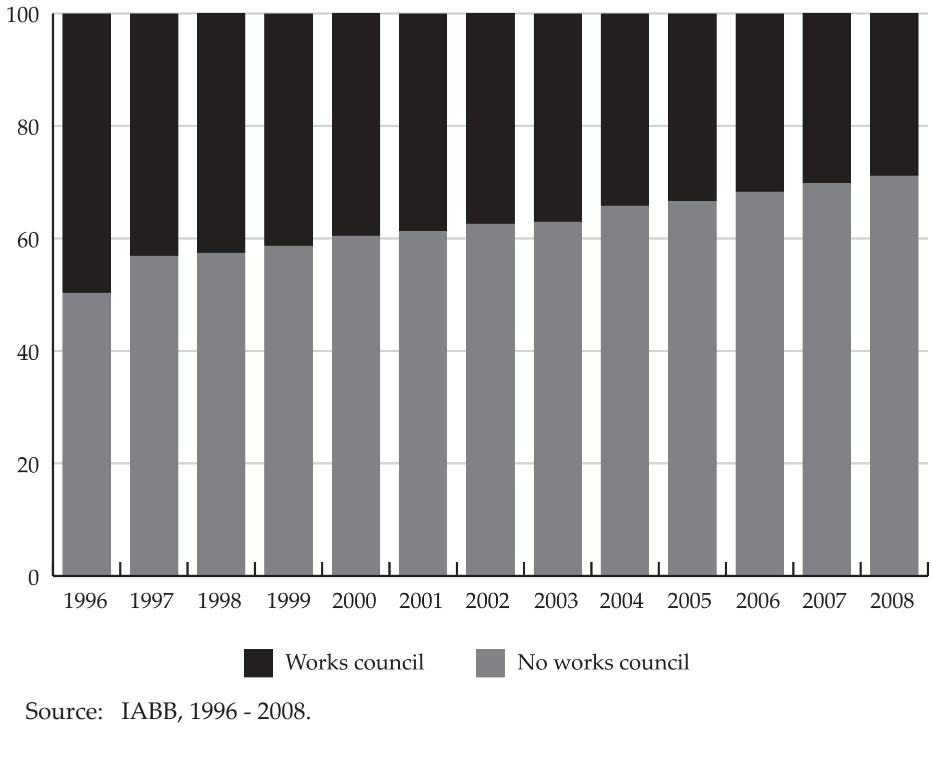
Figure 1.1: Percentage of establishments with agreements at industry level, at company level or without collective agreements from 1996 to 2008.



Source: IABB, 1996 - 2008.

The same, although not quite as strong, is true for the share of establishments with works council, as shown in Figure 1.2.

Figure 1.2: Percentage of establishments with works council from 1996 to 2008.



Source: IABB, 1996 - 2008.

1.6 Empirical model

Our empirical model uses the binary coded variable *Proc* as dependent variable that defines establishments with investments in ICT. Due to the binary coding of the dependent variable, a Random Effects Probit Panel model is used. The model can be written as

$$Prob(\textit{Proc}=1 \mid X) = \Phi\ (X'\beta) + \varepsilon, \tag{3}$$

with X as a vector of independent variables and Φ as the Cumulative Distribution Function of the standard normal distribution. It can be interpreted as the probability of a company to be a process innovator given the variables summarized in X. The vector X contains the binary coded variables *Indlev*, *Complev* and *Nolev*, representing bargaining at industry level, at company level or without collective wage bargaining. Following the first hypothesis, we expect a positive correlation of *Indlev*. In contrast, the association of *Complev* is expected to be negative, according to the second hypothesis. In addition, a number of control variables is included. Accounting for the more cooperative bargaining structure between companies and unions in Germany, as stated by Schnabel and Wagner (1992), we use the variable *Counc* that identifies establishments with works councils. The variable *Exp* as the share of exports in turnover measures the activities in foreign markets. *Resdept* indicates establishments with their own research department. The company's *Size* is measured by the logarithm of the number of employees. *Turn* is the logarithm of the annual turnover. The variable refers to the previous year, so that a possible endogeneity is assumed to be low. The variable *Age* identifies establishments with an age of five years or less. Finally, dummies for the *Region* as well as the individual sectors and years, *Sec* and *Year,* are included. Hence, equation (3) can be written as

$$\begin{aligned} Prob(\textit{Proc}=1 \mid X) = \ & \Phi\ (\beta_0 + \beta_1 \cdot \textit{Indlev} + \beta_2 \cdot \textit{Complev} + \beta_3 \cdot \textit{Counc} + \beta_4 \cdot \\ & \textit{Exp} + \beta_5 \cdot \textit{Resdept} + \beta_6 \cdot \textit{Size} + \beta_7 \cdot \textit{Turn} + \beta_8 \cdot \textit{Age} \\ & + \beta_9 \cdot \textit{Region} + \beta_{10} \cdot \textit{Sec} + \beta_{11} \cdot \textit{Year}). \end{aligned} \tag{4}$$

Considering the assumptions of the theoretical model, equation (4) is calculated again using incremental process innovations *IProc* as dependent variable. The dependent and explanatory variables, their coding and contents are listed in Table 1.3 in the appendix. The results are summarized in the following Chapter 1.7.

1.7 Results

Using the presented data and the empirical model, we obtain the following results. The first column of Table 1.2 summarizes the marginal effects of the Probit Panel regression equation (4) for *Proc*.[10] Compared to decentralized bargaining *Nolev*, wage bargaining at industry level *Indlev* reduces the probability of a process innovation. In contrast, the marginal effect of *Complev* is slightly positive but not significant. The results disprove the first hypothesis, which expects a positive correlation between industry level agreements and process innovations. In addition, the assumed non-linearity of the second hypothesis cannot be found. Bargaining at both levels, *Indlev* and *Complev*, reduces the probability of a process innovation, whereat the marginal effect of *Complev* is smaller and not significant. Moreover, equation (4) shows a significantly negative correlation between the existence of works councils and process innovations.

Table 1.2: Marginal effects of the Panel Probit regression for *Proc* and *IProc*, equation (4).

	(4)					
	Proc			*IProc*		
Indlev	-0.031	(0.007)	***	-0.027	(0.009)	***
Complev	0.006	(0.011)		-0.005	(0.016)	
Nolev	--	--		--	--	
Counc	-0.021	(0.010)	**	$3.13e^{-04}$	(0.013)	
Exp	0.001	($1.90e^{-04}$)	***	$4.25e^{-04}$	($2.50e^{-04}$)	
Resdept	0.117	(0.009)	***	0.101	(0.011)	***
Size	0.081	(0.005)	***	0.061	(0.007)	***
Turn	0.079	(0.004)	***	0.063	(0.005)	***
Age	0.069	(0.009)	***	0.067	(0.011)	***
Region	-0.048	(0.008)	***	-0.063	(0.010)	***
Sec	Yes			Yes		
Year	Yes			Yes		
N	91867			23824		
Chi^2	8843.44***			2105.54***		
Pseudo-R^2	0.54516902			0.68417987		
Log-Likelihood	-48339.96			-12428.165		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: IABB, 1996-2008. Own calculations.

[10] The difficulties in the calculation of the marginal effects are known, particularly when several binary coded explanatory variables are used. The resulting coefficients are listed in Table 1.4 in the appendix.

The second column of Table 1.2 presents the marginal effects of equation (4) using *IProc* as dependent variable. The results hardly change when the analysis is limited to incremental process innovations. Negotiations at industry level *Indlev* significantly reduces the incentives for *IProc*, while the marginal effect of *Complev* is not significant.

The marginal effects of the other independent variables in equation (4) remain relatively constant. Establishments with their own research department *Resdept* have a higher probability of being a process innovator. The same applies to young establishments, which operate internationally. The variables *Turn* and *Size* are also positively correlated with process innovation. In contrast, establishments in Eastern Germany, indicated by *Region*, have a lower probability to implement a process innovation. However, there is a difference in the variable *Counc*. While the existence of a works council is negatively correlated with *Proc*, the marginal effect of *Counc* is positive and no longer significant in a limited analysis.

Studying the effects of unionism on research and innovation could lead to potential problems with endogeneity. It is also conceivable that a company first decides on innovation activities and then chooses a collective bargaining level. In this case, a reverse causality is present, which has been repeatedly discussed in the theoretical as well as the empirical literature (e.g. Hirsch, 1992: 111; Menezes-Filho and Van Reenen, 2003: 305). In order to control for potential problems with reverse causality, equation (4) is calculated using the lagged values of the bargaining levels $Indlev_{t-1}$ and $Complev_{t-1}$ without finding significant differences.[11]

1.8 Conclusions

The relationship between unionism and innovation has already been analyzed several times, whereat the individual bargaining levels have previously not been

11 The results are listed in Table 1.5 in the appendix. Additonally, a correlation matrix of the independent variables as well as additonal descriptive statistics are listed in Table 1.6 and 1.7. The marginal effects and coefficients of the pooled probit regression for process innovations in the years 2007 and 2008 without proxy can be found in Table 1.8.

considered. Using data from German establishments from 1996 to 2008, we find a consistently negative association between union wage bargaining and process innovations. Therefore, we disprove the hypothesis of the theoretical model of Haucap and Wey (2004), which assumes a positive impact of bargaining at industry level. In addition, the assumed non-linearity cannot be found. In fact, collective wage bargaining always reduces the probability of process innovation.

The results can be attributed to changes in the German collective bargaining system. The bargaining situation between unions and companies in countries such as Germany is considerably more cooperative than in the US. This is often cited as a reason why the results from the US often show a negative relationship between unions and innovation, while the results from other countries are rather ambiguous (Schnabel and Wagner, 1992: 370; Menezes-Filho and Van Reenen, 2003: 295). However, rigidities associated with centralized wage bargaining have come under considerable public criticism since several years. As discussed by Brodsky (1994: 55-56), labor market rigidities are assumed to have a negative association with economic efficiency, while decreased centralization and enhanced labor market flexibility, in contrast, are considered to have a positive impact on employment and economic welfare (Bellmann et al., 1999, Wey, 2004 or Brenke, 2004). Therefore, the OECD (2006) supports more flexible options of wage-setting. That is why the number of collective agreements decreased significantly in recent years. In addition, the use of so-called opening clauses is increasing, which allow for company-specific regulations that differ from the bargaining results at industry level (Schnabel, 1999, Hassel, 1999, Addison et al., 2007). In Germany, such exceptions in collective wage agreements become more and more important (Bispinck, 2008). In addition, the number of union members has fallen sharply since the reunion, as noted by Fitzenberger et al. (2006), Schnabel and Wagner (2006) or Goerke and Pannenberg (2007). It is conceivable that the enhanced cooperation between companies and unions in Germany has declined and a potential positive influence of union variables is no longer present.

However, works councils are still strongly represented, even if their existence has also declined (Addison et al., 2007). According to Addison et al. (2004a), more than 50 percent of all German employees were still covered by works councils in 2000.

However, Schnabel and Wagner (1994: 496) also point to the importance of the type of innovation. Product innovations are usually considered as job-creators. Hence, a works council has a particular incentive to support product innovations. Process innovations, in contrast, are assumed to be labor-saving.[12] It can be assumed that works councils have a much lower incentive to support the implementation of process innovations. Our regression results prove this assumption. Indeed, the existence of works councils significantly reduces the probability to implement a process innovation. However, the limited analysis suggests that the negative relationship is not necessarily true for incremental process innovations. The relationship between innovation and works councils is a topic for future research, particularly given the current changes in the wage-bargaining structures (Addison et al., 2004b). In addition, the nature of effect of innovation and labor market characteristics requires more extensive research, which emphasizes the necessity of datasets with comprehensive information on employer and employee level.

[12] A summary of the effects of innovations on employment is given by Vivarelli and Pianta (2000).

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Appendix

Table 1.3: Description of included variables in the regression equations.

Variables	Description	Code
Dependent variables		
Proc	Process innovation	Binary
IProc	Incremental process innovation	Binary
Bargaining variables		
Nolev	No collective bargaining	Binary
Complev	Collective bargaining at company level	Binary
Indlev	Collective bargaining at industry level	Binary
Control variables		
Counc	Establishment has a works council	Binary
Exp	Share of exports in turnover	Percentage
Resdept	Establishment has its own research department	Binary
Size	Logarithm of the number of employees	Continuous
Turn	Logarithm of annual turnover in the previous year	Continuous
Age	Establishment is five years old or younger	Binary
Region	Establishment is located in Eastern Germany	Binary
Sec	Sectors dummies	Binary
Year	Year dummies	Binary

Table 1.4: Coefficients of the Panel Probit regression for *Proc* and *IProc*, equation (4).

	(4)					
	Proc			IProc		
Indlev	-0.078	(0.016)	***	-0.076	(0.028)	***
Complev	0.015	(0.026)		-0.014	(0.047)	
Nolev	--	--		--	--	
Counc	-0.052	(0.023)	**	0.002	(0.037)	
Exp	$1.40e^{-03}$	$(4.86e^{-04})$	***	0.001	(0.001)	
Resdept	0.300	(0.022)	***	0.303	(0.037)	***
Size	0.205	(0.011)	***	0.202	(0.020)	***
Turn	0.199	(0.009)	***	0.183	(0.016)	***
Age	0.177	(0.022)	***	0.229	(0.037)	***
Region	-0.120	(0.018)	***	-0.213	(0.028)	***
Constant	-3.334	(0.106)	***	-2.523	(0.186)	***
Sec	Yes			Yes		
Year	Yes			Yes		
N	91867			23824		
Chi^2	8843.44***			2105.54***		
Pseudo-R^2	0.54516902			0.68417987		
Log-Likelihood	-48339.96			-12428.165		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: IABB, 1996-2008. Own calculations.

Table 1.5: Coefficients of the Panel Probit regression for *Proc* and *IProc* with lagged values, equation (4).

	(4)					
	Proc			IProc		
Indlev_{t-1}	-0.110	(0.019)	***	-0.078	(0.031)	**
Complev_{t-1}	-0.041	(0.029)		0.002	(0.052)	
Nolev_{t-1}	--	--		--	--	
Counc	-0.045	(0.027)	*	-0.015	(0.041)	
Exp	$2.35e^{-03}$	$(5.69e^{-04})$	***	0.002	(0.001)	*
Resdept	0.288	(0.026)	***	0.268	(0.041)	***
Size	0.198	(0.013)	***	0.199	(0.023)	***
Turn	0.230	(0.011)	***	0.211	(0.018)	***
Age	0.082	(0.028)	***	0.123	(0.047)	***
Region	-0.121	(0.021)	***	-0.178	(0.032)	***
Constant	-3.899	(0.127)	***	-3.018	(0.218)	***
Sec	Yes			Yes		
Year	Yes			Yes		
N	72112			23824		
Chi^2	7071.47***			2105.54***		
Pseudo-R^2	0.65065098			0.68417987		
Log-Likelihood	-37152.983			-12428.165		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: IABB, 1996-2008. Own calculations.

Table 1.6: Correlations of the independent variables.

	Indlev	Complev	Size	Turn	Region	Resdept	Age	Exp	Counc
Indlev	1								
Complev	-0.233	1							
Size	0.333	0.168	1						
Turn	0.334	0.157	0.915	1					
Region	-0.226	0.058	-0.161	-0.199	1				
Resdept	0.078	0.086	0.435	0.429	-0.058	1			
Age	-0.083	-0.020	-0.111	-0.125	-0.004	-0.024	1		
Exp	0.089	0.038	0.389	0.421	-0.139	0.458	-0.028	1	
Counc	0.328	0.207	0.682	0.681	-0.126	0.372	-0.080	0.329	1

Source: IABB, 1996-2008. Own calculations.

Table 1.7: Mean and standard deviation of the additional control variables.

Variables	N	Mean	Std. Dev.
Size	178783	3.3939	1.9245
Turn	121577	14.4732	2.2711
Age	205965	0.0784	0.2688
Exp	166220	6.4391	17.3951

Source: IABB, 1996-2008. Own calculations.

Table 1.8: Marginal effects and coefficients of the Pooled Probit regression for *Proc* without proxy for the years 2007 and 2008, equation (4).

	Proc, (4)					
	Marginal effects			Coeffcients		
Indlev	-0.016	(0.007)	**	-0.108	(0.046)	**
Complev	0.005	(0.012)		0.029	(0.076)	
Nolev	--	--		--	--	
Counc	-0.004	(0.009)		-0.029	(0.060)	
Exp	5.34e-04	(1.70e-04)	***	3.41e-03	(1.08e-03)	***
Resdept	0.236	(0.018)	***	1.009	(0.061)	***
Size	0.034	(0.005)	***	0.216	(0.030)	***
Turn	0.018	(0.004)	***	0.118	(0.024)	***
Age	0.049	(0.012)	***	0.272	(0.060)	***
Region	-0.056	(0.007)	***	-0.371	(0.044)	***
Constant				-3.891	(0.284)	***
Sec	Yes			Yes		
Year	Yes			Yes		
N	17747					
Chi^2	3542.00***					
Pseudo-R^2	0.1872					
Log-Likelihood	-7689.7294					

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: IABB, 1996-2008. Own calculations.

2 Wage bargaining and product innovation About the allocation of research resources

This paper gives attention to the relationship between different wage bargaining levels and product innovations using German establishment data from 1996 to 2008. The influence of unionism on innovation is a long discussed issue. Nevertheless, the different bargaining levels have so far been neglected. Following a theoretical model, the incentives for introducing process innovations are highest in bargaining at industry level and lowest in bargaining at company level. Using an extension of the model, I argue that an increased incentive for process innovations leads to fewer resources available for the development of new products. However, the regression results show a consistently negative association between the different wage-setting levels and product innovations, especially in the case of a radical product innovations. The existence of works councils, in contrast, is positively correlated with product innovations. However, the result is only true for incremental product improvements. Instead, works councils have lower incentives to support radical product innovations.

2.1 Introduction

Labor unions and their impact on different micro- and macroeconomic factors – as well as on innovation – have already been investigated several times. In the field of innovation research, the focus has mostly been on the influence of unionism on the level of research spending (Menezes-Filho and Van Reenen, 2003).

Theoretically, the impact of unionism is not unambiguous. Following Freeman and Medoff (1979, 1984) unions have two main effects with different directions. On the one hand, unions can use their market power to increase the wages of their members, which causes potential distortions. On the other hand, unions form a necessary representation of the employees in order to prevent inequalities. The so-called collective voice may improve the relationship between employee and employer and result in an increased productivity (Freeman and Medoff, 1979, 1984). Hence, arguments for either a negative or a positive relationship can be found. Which effect predominates is therefore an empirical question. Previous studies on the relationship between unionism and profits mostly suggest a negative correlation. Unions reduce the returns from investments by so-called rent-seeking. According to Hirsch and Link (1987), this particularly concerns investments in intangible assets such as research and development (R&D) and innovation. Empirical studies have mostly found a negative correlation for data from the United States (US), while the results for European countries are rather ambiguous (Menezes-Filho and Van Reenen, 2003: 311-312).

This paper analyzes the association between different wage bargaining levels and innovation, using the implementation of product innovations instead of research expenditures as the dependent variable. In addition, a subdivision into incremental and radical innovation is made. Therefore, it can be investigated whether the impact of bargaining levels varies by type of innovation. It turns out that collective wage bargaining is always negatively associated with product innovations.

The rest of the paper is structured as follows. Chapter 2.2 briefly summarizes the theoretical approaches about the relationship between unionism and innovation. The following Chapter 2.3 gives an overview of previous studies. Chapter 2.4 presents the theoretical model, based on two existing models. The data and empirical approach to test the derived hypotheses is subject of Chapter 2.5 and 2.6, respectively. Chapter 2.7 summarizes the results. Finally, some conclusions are given in Chapter 2.8.

2.2 Unionism and innovation

The relationship between unionism and innovation is not unambiguous. Historically, unions are often classified as a technology-averse (Menezes-Filho and Van Reenen, 2003: 294). In contrast, Freeman and Medoff (1979, 1984) points to the importance of unions as a collective voice which can help to adapt new technologies by the increase of moral and motivation. In addition, mainly three different effects are discussed that provide arguments for either a positive or a negative relationship.[1]

The most commonly assumed theoretical relationship is based on the hold-up effect according to the model of Grout (1984) and the considerations of Simons (1944). Following this so-called rent-seeking approach, a union acts like a tax on intangible capital returns to receive a share of quasi-rents of a company (e.g. Hirsch and Link, 1987: 323; Menezes-Filho and Van Reenen, 2003: 296; Connolly et al., 1986: 567). After the implementation of an innovation, a union sets higher wages in order to get a share of the innovation profits. Thereby, the expected profits after the innovation will decrease. The innovation gains can be zero, if the wages increase to the same extent as the cost reduction or the turnover enhancement as a result of the innovation. Before the investment, the union cannot credibly demonstrate, not to raise the wages after innovation. The anticipation of this hold-up situation decreases the incentives of a company to invest in innovation and leads to a lack of investments (Grout, 1984: 449; Menezes-Filho and Van Reenen, 2003: 296). Theoretically, a hold-up problem can occur with any kind of investment. However, investments in intangible capital such as R&D are particularly affected due to the associated high share of sunk costs (Menezes-Filho and Van Reenen, 2003: 296). As stated by Connolly et al. (1986), R&D investments are particularly affected by a possible rent-seeking if

[1] A summary of the theoretical approaches is given by Menezes-Filho and Van Reenen (2003).

the following innovation cannot be licensed or patented, which usually cannot be assessed before the investment. However, the negative hold-up effect can also be reduced. The negotiations between unions and companies take place repeatedly. Following Van der Ploeg (1987), unions could lose their reputation as a consequence of rent-seeking and have an incentive to cooperate. Ulph and Ulph (1998) also refer to long-term contracts and cooperative bargaining to reduce the rent-seeking.

Following the strategic effect, in contrast, a company has an inventive to invest in R&D in to order to obtain a competitive advantage. Unionism even increases the incentive, because of the disadvantaged position of the non-innovating company after collective bargaining (Lingens, 2009: 261; Menezes-Filho and Van Reenen, 2003: 299-301). Finally, Lingens (2009) establishes the Arrow effect that occurs during the development phase. Collective bargaining reduces the profits during the research time. Hence, the Arrow effect increases the incentives to invest in R&D in order to shorten the time before implementation. However, the hold-up effect dominates in the model of Lingens (2009), so that collective bargaining always reduces the innovation incentives.

According to the theory, arguments for either a positive or a negative relationship between unionism and innovation can be found. Which effect ultimately dominates is an empirical question.

2.3 Literature review

Most of the previous empirical studies assume a negative relationship between unionism and innovation based on the rent-seeking model. In most cases, the expenditures on R&D are used as dependent variable. The R&D expenditures are an input factor and an indirect measurement of innovation. The variable measures the effort, which is operated to generate an innovation. It is often available in surveys and can be easily interpreted due to its monetary definition (Menezes-Filho and Van Reenen, 2003: 301-302). However, the R&D expenditures do not provide any information on the results of the research efforts or their quality. Whether R&D expenditures lead to a successfully implemented innovation, cannot be guaranteed

(Menezes-Filho and Van Reenen, 2003: 301). A further disadvantage is the frequent high number of missing values or the under-reporting of small and medium-sized companies (Menezes-Filho and Van Reenen, 2003: 302).[2] These problems can be avoided with the use of directly measured innovation variables, which represent the output of research such as the number of patents or innovations, the introduction of products and processes or the diffusion of new technologies.

Most of the studies that use the research expenditures as dependent variable show a negative relationship between unionism and innovation. This is particularly true for studies with data from the US. Following the analysis of Connolly et al. (1986), unionism significantly reduces the R&D intensity of US companies. Similar results are found by Hirsch (1992) or Bronars et al. (1994), although the relationship seems to depend on the considered sectors. The results of studies using European data are rather ambiguous. Using data from the United Kingdom (UK), Menezes-Filho et al. (1998) also show a negative correlation, which is no longer significant after the inclusion of all control variables. Schnabel and Wagner (1994) cannot find a significant association in German industries. According to the results of Ulph and Ulph (1989), unionism is even positively associated with R&D in low-tech sectors in the UK.

Empirical studies with a direct innovation measurement as dependent variable are comparatively rare. Acs and Audretsch (1988) use the number of innovations collected from US trade journals. Their results show a negative and significant correlation of unionism measured by union density. Similar results are found by Blundell et al. (1999) using data from the UK. Machin and Wadhwani (1991) use data from the US Workplace Industrial Relations Survey (WIRS). Following their results, no significant association between unionism and the introduction of conventional and advanced technological changes can be found. Hirsch and Link (1987) analyze the specific impact of unionism on product innovations. Using firm level data from the US, they estimate several Ordered Probit models. The dependent variables are scaled and illustrate the company's own assessment of the use and development of product innovations compared to competitors. The results show significantly lower

2 See also Kleinknecht (1996) for more information.

scale values in companies with a union coverage of more than 50 percent. Using works councils and the difference between industry agreements and the wages paid at the company level to measure unionism, Schnabel and Wagner (1992) find a positive and significant correlation with product innovations in Germany. However, the results are only significant without controlling for company size.

Regardless of whether an indirect or direct measurement is used as dependent variable, it turns out that most of all studies from the US prove a negative relationship between unionism and innovation in contrast to the results from other countries such as Germany. The differences can be attributed to the bargaining structure. The negative rent-seeking approach is based on inefficient bargaining between unions and companies. Following Schnabel and Wagner (1992), the more cooperative relationship in countries, such as Germany, may lead to more efficient negotiations and innovation-friendly framework conditions. For example, the existence of works councils can be considered as an opportunity for the advanced communication between employers and employees. In the long run, companies and unions benefit from innovations and have therefore an incentive to support it. As stated by Schnabel and Wagner (1992), this might be especially true for product innovations that are considered to be job-creators. However, it is not clear whether a linear positive relationship can be assumed for all levels of wage bargaining.

2.4 Theoretical model

The theory of this paper is based on two theoretical models. The fundamental assumptions about the interaction between the levels of collective bargaining and innovation incentives stem from the model of Haucap and Wey (2004). In a further step, the model of Boone (2000) is used for a theoretical extension.

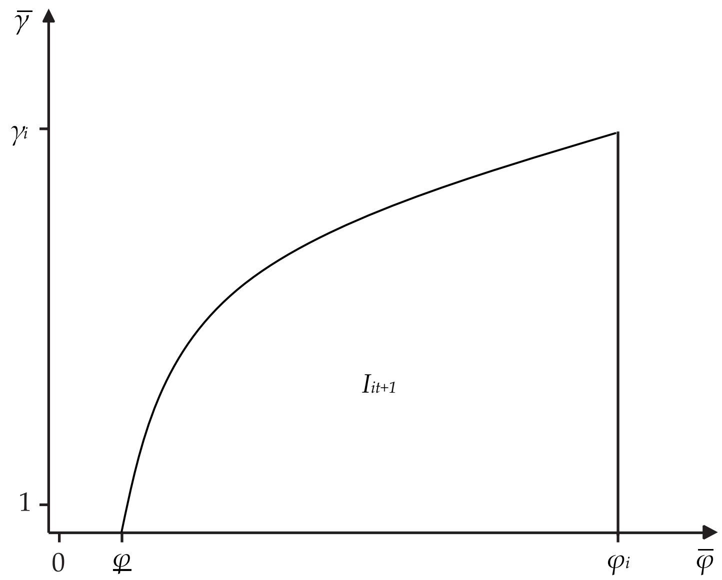
The theoretical model of Haucap and Wey (2004) establishes a theoretical relationship between different levels of wage bargaining and investment in process innovations. The main thesis of the model shows that a centralized wage-setting at the industry level has a positive effect on the development of a process innovation. Wages negotiated at industry level are established according to the productivity of all firms in one sector. After a successful process innovation of a single company, the accumulated sector productivity increases and the wage level increases consequently. However, the wages do not rise to the same extent as the cost savings as a result of innovation. In this way, the innovating firm does not lose its entire profits from innovation. In contrast, the union sets the wage level according to the productivity of a single company if the wage bargaining takes place at company level. If the productivity rises as a part of the process innovation, the wage of the innovating company will increase in the same way. The company loses the gains of the cost-saving process innovation. Thus, there are no incentives to invest in innovation. Following Haucap and Wey (2004), a coordinated wage-setting at company level affects negatively and the influence of the degree of wage bargaining centralization is not linear. In addition, a further argument explains the positive effect of industry level bargaining. The wages for all companies in an industry are on the same level with centralized wage-setting. In this case, cost reductions and thus competitive advantages can only be achieved by developing a cost-efficient production process.

Haucap and Wey (2004) only consider the relationship with process innovations. But how does the bargaining centralization affect product innovations? A separate model for product improvements or the introduction of an entirely new product has not yet been developed. Therefore, I establish a new model approach to transfer the previously described hypotheses. The model is based on the theoretical background of Haucap and Wey (2004) and integrates a more general growth model of Boone (2000). It can be shown that, depending on the bargaining level, companies will focus on a certain type of innovation. In the model of Boone (2000), the form of an innovation is considered as endogenous. He distinguishes between a cost reduction and a quality increase. A company has only a limited amount of resources such as financial or human capital resources. For example, the capacity of research staff is limited to the number of workers. Working hours invested in cost reduction can no longer be used to improve the quality. Therefore, a company has to decide on allocating its resources. According to Boone (2000), a company proceeds as follows. At time t each firm i has a certain set of possibilities I_{it+1} for an innovation at time $t+1$.[3]

[3] Boone (2000) assumes that the incumbent is the innovating company, while most of the previous

An innovation has the two different dimensions, quality q_{it} and costs f_{it}. Labor and capital are the only input variables. The company can choose to invest its resources in increasing the quality or lowering the production costs. The innovation opportunities lie between these dimensions according to quality q_{it} and costs f_{it}. Figure 2.1 shows the possible set of innovations for a company at time $t+1$. The quality of a product can be increased by a factor γ_i, shown on the y-axis. Opportunities for innovation with respect to reducing the costs by a factor φ_i are given on the x-axis.

Figure 2.1: Possible set of innovation.



Source: Boone (2000: 588).

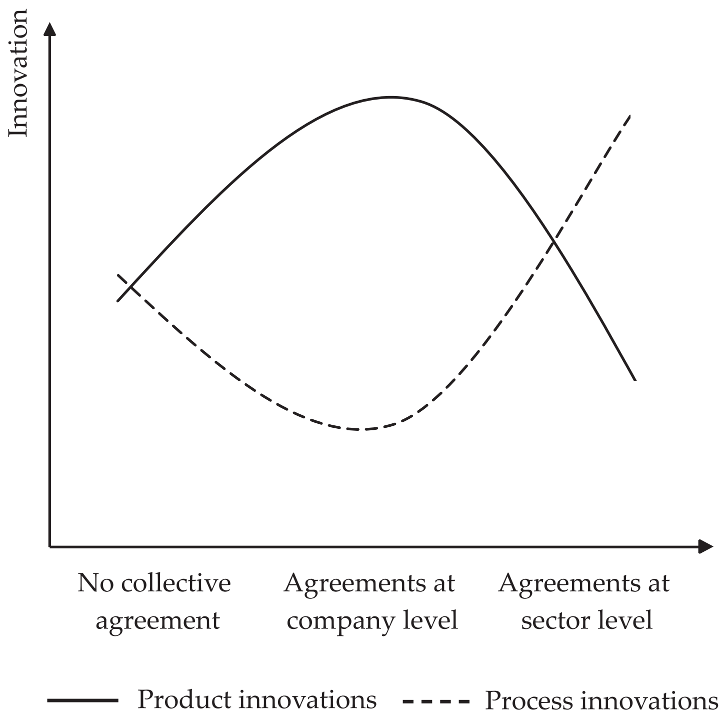
This set of innovation opportunities is not fixed in time. In addition, the allocation decision depends on the research focus of the individual company or on the industry the company belongs to. The innovation opportunities are limited in both dimensions. On the one hand, an innovation cannot reduce the quality of a product. Therefore, γ is at least 1. On the other hand, the costs cannot be reduced to zero by an innovation. Therefore, the set starts at $\underline{\varphi}$ and $\varphi_i \geq \underline{\varphi} > 0$ holds. However, a product innovation can increase the costs, for example by recruiting new personnel or by increasing the research expenditures. Therefore, $\varphi_i > 1$ may apply. Figure 2.1 shows that the more a company tries to reduce its costs, the less it can focus on improving the quality and vice versa.[4]

studies consider the entrant as innovator. Empirical studies show that neither of these assumptions is to be preferred. See Boone (2000: 588) or Tirole (1988: 305-352) .

4 This was also found by Dougherty and Bowman (1995: 30).

In which way does a union influence this allocation decision? According to the model of Haucap and Wey (2004), a company with centralized wage-setting has the highest incentive to invest in cost-reducing process innovations. A collective wage-setting at company level, however, will rather reduce the investments in process innovations. Following the assumptions of Boone (2000), these results also affect the investments in product innovations. The stronger the incentive for process innovations, the more a company will invest in cost-saving new technologies. In this case, only a few or even no resources remain for an increase in quality and vice versa. The relationship between the wage-setting levels and product innovations, therefore, is exactly the reverse of the association with process innovations. Following Haucap and Wey (2004), the relationship between the wage bargaining centralization and process innovations is U-shaped. The incentives are lowest in wage-setting at company level and highest in industry negotiations. In contrast, the correlation with product innovations is approximately an inverted U-shaped function. That means the incentives to invest in product innovations are lowest in bargaining at industry level and highest in bargaining at company level, as shown in Figure 2.2.

Figure 2.2: Theoretical relationship between the levels of wage bargaining and process and product innovation.



Source: Haucap and Wey (2004: C152) and Boone (2000: 589).

Following the theoretical assumptions, three hypotheses can be derived.

Hypothesis I Collective agreements, which are negotiated at industry level, have the lowest incentive to invest in product innovations.

Hypothesis II Analogous to process innovations, the relationship between collective bargaining and product innovations is not linear. Wage bargaining at company level leads to the highest incentive to invest in product innovations.

The model of Boone (2000) considers product innovations as quality improvements. This assumption leads to the question of whether the relationship depends on the type of product innovation. Following the Oslo Manual of the OECD (2005), incremental innovations lead the way in small continuous steps, while radical innovations represent large and soaring changes. An incremental product innovation improves an existing product in terms of better or additional performances. It represents merely a change in the existing production function. In contrast, a radical product innovation represents a completely new product whose technological characteristics or applications differ significantly from those of previously manufactured products. It can be a novelty for a company or for the entire market and includes the addition of an already existing product on the market in the range of a company or the introduction of an entirely new product (OECD, 2005: 31-32). It can be assumed that radical innovations require more resources than incremental innovations. Hence, an increased incentive to invest in process innovations does not necessarily lead to a sharp decline in product changes.

Hypothesis III The impact will be stronger, the more the product innovation will change the production function of a company. Hence, if a product is new to the company or even new to the market, the correlation will be strongest. In contrast, the association is lower if the innovation changes only product details.

The data and the regression model are presented in the following Chapters 2.5 and 2.6, respectively.

2.5 Data

The data basis of this paper is the Establishment Panel of the Institute for Employment Research (IABB), wave 1996 to 2008. The data access was carried out by controlled remote data processing at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA).[5] As the only dataset in Germany, the IABB gives information about bargaining levels of around 16,000 establishments. It is a representative survey for all sectors and sizes, collected in Western and Eastern Germany since 1996. The meaning of the turnover variable in the dataset is ambiguous. The variable can include the turnover, the total assets, the total premiums paid or the budget volume. Due to deviations in the meaning of turnover, the banking and insurance industry, non-profit as well as public administration organizations are excluded. All monetary variables are given in Euro (€).

Product innovations are included in the dataset in different types. A product innovation can be either the improvement of an existing product, the addition of an existing product on the market in the range of a company or the development of an entirely new product. Following the officially established definitions of the OECD (2005), establishments with product improvements are designated as incremental product innovators. In contrast, establishments with a product addition or a newly developed product are considered as radical product innovators.

Table 2.1 summarizes some descriptive statistics. In the considered time period, the share of product innovators is 44 percent. The most common type of innovation is a product improvement. More than 38 percent of all observed establishments have introduced at least one improved product. Nearly 22 percent have added a product to their assortment. Only about nine percent of all observations have successfully introduced an entirely new product.[6] Establishments that have adopted incremental product innovations represent about 18 percent of the dataset. Round about 30 percent of the establishments are radical product innovators.

[5] Further information on the data, the variables and the encoding can be found at Städele and Müller (2006).

[6] Due to the fact that a company can implement several innovations by different type in the same year, the sum of the percentage points is not 100.

Table 2.1: Summary of descriptive statistics, percentage.

Descriptive Variables	All	Product innovators	Incremental innovators	Radical innovators
Product innovators	43.44			
Product improvement	38.21			
Product addition	21.77			
Entirely new product	8.83			
Incremental product innovation	18.01			
Radical product innovation	30.98			
Sectors				
Consumer goods	9.27	10.01	11.47	9.03
Nutrition	3.10	4.22	3.59	4.65
Producer goods	11.05	15.97	16.25	15.78
Machine construction	3.52	5.66	6.22	5.29
Investment goods	8.09	10.35	9.66	10.83
Trade	16.77	15.2	10.18	18.61
Transportation	5.38	4.08	5.35	3.22
Business services	8.15	8.52	8.81	8.31
Technical services	15.57	10.77	10.38	11.03
Other services	12.31	9.20	10.49	8.32
Real estate	6.79	6.01	7.60	4.93
Total	100.00	100.00	100.00	100.00
Employment size				
Less than 10	32.68	21.45	20.00	22.34
10 to under 25	16.61	15.42	14.40	16.15
25 to under 50	12.37	13.22	12.97	13.40
50 to under 250	22.32	27.31	28.09	26.76
250 and more	16.01	22.59	24.35	21.34
Total	100.00	100.00	100.00	100.00
Region				
Western Germany	55.98	61.02	64.32	58.67
Eastern Germany	44.02	38.98	35.68	41.33
Total	100.00	100.00	100.00	100.00
R&D department				
No own R&D department	84.61	70.23	73.03	68.24
Own R&D department	15.39	29.77	26.97	31.76
Total	100.00	100.00	100.00	100.00
Employee representation				
No works council	63.86	53.92	50.47	56.37
Works council	36.14	46.08	50.00	43.63
Total	100.00	100.00	100.00	100.00
Collective bargaining				
Agreements at sector level	46.39	48.24	39.28	43.85
Agreements at company level	8.26	9.81	10.16	9.55
No collective agreements	45.35	41.95	51.00	46.6.0
Total	100.00	100.00	100.00	100.00

Source: IABB 1996-2008.

The trade and producer goods as well as the technical and other services are the most common sectors in the dataset. Nearly one-third of all establishments have less than ten employees. The share of large establishments with 250 or more employees, however, is only half as large. In contrast, up to 50 percent of the innovators have at least 50 employees. More than 55 percent of all observations are located in Western Germany. The percentage is even higher for product innovators and especially for incremental product innovators. More than three-quarters of the observations do not have their own research department, while the share is twice as high for product innovators. More than 60 percent of all establishments have no works council. The share is significantly lower in innovating establishments. More than half of all establishments pay a collectively negotiated wage. Thereby, bargaining at industry level is much more common than company level agreements. The proportion of collectively bargained wages is even higher for innovators, especially for incremental product innovators. However, the share of collectively negotiated wages decreases during the observed time period. Figure 1.1 on page 12 shows the percentage of agreements at industry and at company level as well as the percentage of establishments without collective agreements from 1996 to 2008. Although not quite as strong, the percentage of establishments with works councils decreases as well, as shown in Figure 1.2 on page 12.

2.6 Empirical model

The presented data is used to calculate a binary coded Random Effects Panel Probit model. The dependent variable is the successful implementation of a product innovation *Prod*. The model can be written as

$$Prob(\textit{Prod}=1 \mid X) = \Phi\ (X'\beta) + \varepsilon, \tag{1}$$

with X as a vector of independent variables and Φ as the Cumulative Distribution Function of the standard normal distribution. It can be interpreted as the probability of a company to be a product innovator given the variables summarized in X. The following variables are used as independent variables in the vector X. The collective bargaining agreements are included as binary coded variables, indicating establishments with negotiations at industry level *Indlev* and at company level *Complev* compared to no collective agreements *Nolev*. To account for cooperative strategies between companies and unions and the resulting potentially improved innovation conditions, as stated by Schnabel and Wagner (1992), the variable *Counc* is used to identify establishments with works councils. The effects of the national wage system are stronger, the less a company operates in foreign markets with different wage structures. Therefore, the share of exports in turnover *Exp* is included. The research behavior is represented by the variable *Resdept*, which identifies establishments with their own research department. The *Size* of a company is measured by the logarithm of the number of employees. The logged annual turnover is given by *Turn*. The variable refers to the previous year, so that a possible endogeneity can assumed to be low. The variable *Age* identifies establishments with an age of five years or less. A regional variable *Region* is integrated into the model to account for the remaining differences between companies in Eastern and Western Germany. Finally, I include the dummies *Sec* and *Year* to control for different innovation conditions in the individual sectors and years, respectively. Equation (1) can be written as

$$Prob(\mathit{Prod}=1|X) = \Phi\,(\beta_0 + \beta_1 \cdot \mathit{Indlev} + \beta_2 \cdot \mathit{Complev} + \beta_3 \cdot \mathit{Counc} + \beta_4 \cdot \mathit{Exp} + \beta_5 \cdot \mathit{Resdept} + \beta_6 \cdot \mathit{Size} + \beta_7 \cdot \mathit{Turn} + \beta_8 \cdot \mathit{Age} + \beta_9 \cdot \mathit{Region} + \beta_{10} \cdot \mathit{Sec} + \beta_{11} \cdot \mathit{Year}) \quad (2)$$

For a subsequent separate calculation of the individual innovation types, equation (2) is additionally calculated using the binary variables for incremental *IProd* and radical product innovations *RProd* as dependent variables. As mentioned, product improvements are considered as incremental product innovations. In contrast, product additions and completely new products form a new production function and are therefore classified as radical innovations. The dependent and explanatory variables, their coding and contents are listed in Table 2.3 in the appendix. The results are summarized in the following Chapter 2.7.

2.7 Results

The regression results for *Prod* as well as for *IProd* and *RProd* are listed in Table 2.2. Considering all product innovations, equation (2) shows a continuously and significantly negative relationship between the collective bargaining levels and the probability of product innovation. Thereby, the marginal effect of industry level agreements *Indlev* is slightly higher.[7] Thus, agreements at industry level *Indlev* have the lowest incentives, while no wage bargaining *Nolev* has the highest incentives to implement a product innovation. This result confirms the first hypothesis, assuming a negative correlation of *Indlev*. At the same time, the result disproves the second hypothesis, which assumes a positive correlation between a product innovation and *Complev*. Hence, the expected non-linearity cannot be found. In contrast to the negative marginal effects of the bargaining levels, the existence of a works council *Counc* is positively associated with product innovations.

Table 2.2: Marginal effects of the Panel Probit regression for *Prod*, *IProd* and *RProd*, equation (2).

	(2)								
	Prod			*IProd*			*RProd*		
Indlev	-0.057	(0.009)	***	-0.005	(0.002)	***	-0.017	(0.004)	***
Complev	-0.025	(0.014)	*	-0.002	(0.002)		-0.007	(0.005)	*
Nolev	--	--		--	--		--	--	
Counc	0.014	(0.014)		0.004	(0.002)	*	0.002	(0.006)	
Exp	0.004	(3.20e-04)	***	2.08e-04	(4.00e-05)	***	0.001	(1.20e-04)	***
Resdept	0.486	(0.009)	***	0.017	(0.003)	***	0.215	(0.010)	***
Size	0.098	(0.007)	***	0.009	(0.001)	***	0.021	(0.003)	***
Turn	0.069	(0.006)	***	0.005	(0.001)	***	0.020	(0.002)	***
Age	0.073	(0.013)	***	0.002	(0.002)		0.032	(0.006)	***
Region	-0.098	(0.014)	***	-0.017	(0.002)	***	-0.003	(0.006)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	92461			92688			75299		
Wald-Chi^2	6222.19***			1813.04***			5778.85***		
Pseudo-R^2	0.43367342			0.39469017			0.4222795		
Log-Likelihood	-39786.688			-33278.144			-28173.749		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %
Source: IABB, 1996-2008. Own calculations.

The existence of a firm's own R&D department *Resdept* greatly increases the probability of product innovation. The variables *Exp*, *Size* and *Turn* also have a positive association. Young companies have a higher probability to be a product innovator.

7 The difficulties in the calculation of the marginal effects are known, particularly when several binary coded explanatory variables are used. The resulting coefficients are listed in Table 2.4 in the appendix.

In contrast, companies in Eastern Germany are less likely to successfully implement a product innovation.

Does the effect of different bargaining levels on the innovative behavior change according to the different types of product innovation? To answer this question, the Panel Probit equations (2) is calculated again with a distinction between incremental and radical innovation. The results in Table 2.2 show that *Indlev* and *Complev* are negatively correlated with product innovation, regardless of whether it is a radical or an incremental one.

However, a significant difference can be found in the variable *Counc*. While the existence of works councils has a positive association with the development of incremental product innovations, the marginal effect of *Counc* is much lower and not significant for radical product innovations. In addition, the other control variables show some interesting differences between *IProd* and *RProd*. The *Age* of an establishment is more strongly associated with radical product innovations, while the *Region* is more negatively correlated with incremental product innovations. Furthermore, research and investments are more important for radical product innovations. The marginal effect of *Turn* is more than twice as high and the marginal effect of *Resdept* is even eight times larger than the one for incremental innovations.

Studying the effects of unionism on research and innovation could lead to potential problems with endogeneity. It is also conceivable that a company first decides on innovation activities and then chooses a collective bargaining level. In this case, a reverse causality is present, which has been repeatedly discussed in the theoretical as well as the empirical literature (Hirsch, 1992: 111; Menezes-Filho and Van Reenen, 2003: 305-306 or Lu et al., 2010: 208-209). Therefore, equation (2) is calculated again using the lagged values of the bargaining levels. Neither the height of the marginal effects nor the significance levels changes. Thus, the previously described results can be confirmed and the presence of a possible reverse causality can assumed to be low.[8]

[8] The results can be found in Table 2.5 in the appendix. Additonally, a correlation matrix of the independent variables as well as additonal descriptive statistics can be found in Table 2.6 and 2.7.

2.8 Conclusions

The relationship between unionism and innovation has often been studied theoretically and empirically. In most cases, negative results have been found, especially for the US. The different wage bargaining levels as a measurement of union power were not considered yet. In this paper, it can be shown that the individual levels are negatively associated with product innovations. Collective wage bargaining, particularly at the industry level, reduces the probability of successfully implemented product innovations. The results confirm the first hypothesis, which assumes a negative relationship between bargaining at industry level and product innovations. However, the assumed non-linearity of the second hypothesis cannot be found. In contrast, any collective wage bargaining is negatively correlated with product innovation. This is especially true for radical product innovations.

The reason for the continuously negative relationship may lie in the changes of the German wage bargaining system. The bargaining situation between unions and companies in countries such as Germany is considerably more cooperative than in the US. This is often cited as a reason why the results from the US often show a negative relationship between unionism and innovation, while the results from other countries are rather ambiguous (Schnabel and Wagner, 1992: 370; Menezes-Filho and Van Reenen, 2003: 295). However, the share of collective wage bargaining in Germany has declined over the last 20 years. For several years, rigidities associated with centralized wage bargaining have come under considerable public criticism (Brodsky, 1994: 55-56; Tüselmann, 2001: 547). The demand for increased wage flexibility has led to a decline in industry negotiations and an increase of so-called opening clauses (Hassel, 1999; Schnabel, 1999; Addison et al., 2007). These clauses allow company-specific regulations that differ from the bargaining results at industry level. In Germany, such exceptions in collective wage agreements become more and more important (Schnabel, 1999; Bispinck, 2008). In addition, the number of union members has fallen sharply since the reunion, as noted by Fitzenberger et al. (2006), Schnabel and Wagner (2006) or Goerke and Pannenberg (2007). It is conceivable that the enhanced cooperation between companies and unions in Germany has declined and a potential positive influence of union variables is no longer present.

In contrast, works councils are still strongly represented, even if their existence has also declined. According to Addison et al. (2004), more than 50 percent of all German employees were still covered by works councils in 2000. As stated by Schnabel and Wagner (1992), works councils can especially improve the communication between companies and unions, and thus influence the innovation behavior of a company. This can be found in a positive correlation between the existence of works councils and product innovations. Unions as well as works councils have an incentive to support job-creating product innovations.[9] However, the positive association does not apply to all types of product innovation. While works councils are positively correlated with incremental product innovations, the marginal effect for radical innovations is negative and not significant. Radical product innovations mostly require higher research expenditures, as shown by the regression marginal effects of *Turn* and *Resdept*, and are therefore associated with higher risks for a company and its employees. Hence, the incentive to support radical product innovations might be less.

The results show that a cooperative bargaining system, as represented by works councils, can support the incentives for innovation. Eventually, the negative union effects are partly captured by the positive cooperation effects of works councils. To support the cooperative bargaining in Germany, the collective bargaining system should be stabilized, as already requested by researchers such as Wey (2004: 150-151). The development of the characteristics and the institutions on the labor market, for example by opening clauses, and their impact on innovation is an interesting topic for future research, requiring panel datasets that bring together information on employer and employee level.

9 A summary of the effects of innovations on employment is given by Vivarelli and Pianta (2000).

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Appendix

Table 2.3: Description of included variables in the regression.

Variables	Description	Code
Dependent variables		
Prod	Product innovation	Binary
IProd	Incremental product innovation	Binary
RProd	Radical product innovation	Binary
Bargaining variables		
Nolev	No collective bargaining	Binary
Complev	Collective bargaining at company level	Binary
Indlev	Collective bargaining at industry level	Binary
Control variables		
Counc	Establishment has a works council	Binary
Exp	Share of exports in turnover	Percentage
Resdept	Establishment has its own research department	Binary
Size	Logarithm of the number of employees	Continuous
Turn	Logarithm of annual turnover in the previous year	Continuous
Age	Establishment is five years old or younger	Binary
Region	Establishment is located in Eastern Germany	Binary
Sec	Sectors dummies	Binary
Year	Year dummies	Binary

Table 2.4: Coefficients of the Panel Probit regression for *Prod*, *IProd* and *RProd*, equation (2).

	(2)								
	Prod			*IProd*			*RProd*		
Indlev	-0.143	(0.023)	***	-0.083	(0.025)	***	-0.173	(0.030)	***
Complev	-0.063	(0.036)	*	-0.029	(0.037)		-0.077	(0.045)	*
Nolev	--	--		--	--		--	--	
Counc	0.036	(0.036)		0.064	(0.037)	*	0.006	(0.047)	
Exp	0.010	(0.001)	***	0.003	(0.001)	***	0.012	(0.001)	***
Resdept	1.390	(0.035)	***	0.237	(0.030)	***	1.870	(0.046)	***
Size	0.246	(0.018)	***	0.147	(0.019)	***	0.258	(0.023)	***
Turn	0.173	(0.014)	***	0.084	(0.015)	***	0.205	(0.019)	***
Age	0.184	(0.032)	***	0.034	(0.033)		0.233	(0.041)	***
Region	-0.248	(0.035)	***	-0.288	(0.035)	***	-0.155	(0.045)	***
Const	-3.707	(0.174)	***	-3.134	(0.178)	***	-5.465	(0.226)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	92461			92688			75299		
Chi^2	6222.19***			1813.04***			5778.85***		
Pseudo-R^2	.43367342			0.39469017			0.4222795		
Log-Likelihood	-39786.688			-33278.144			-28173.749		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %
Source: IABB, 1996-2008. Own calculations.

Table 2.5: Coefficients of the Panel Probit regression for *Prod*, *IProd* and *RProd* using the lagged values, equation (2).

	(2)								
	Prod			*IProd*			*RProd*		
Indlev$_{t-1}$	-0.142	(0.026)	***	-0.133	(0.028)	***	-0.119	(0.033)	***
Complev$_{t-1}$	-0.069	(0.039)	*	-0.068	(0.040)	*	-0.058	(0.050)	
Nolev$_{t-1}$	--	--		--	--		--	--	
Counc	0.018	(0.040)		0.074	(0.040)	*	-0.015	(0.052)	
Exp	0.011	(0.001)	***	0.003	(0.001)	***	0.013	(0.001)	***
Resdept	1.352	(0.039)	***	0.240	(0.034)	***	1.804	(0.052)	***
Size	0.233	(0.020)	***	0.124	(0.021)	***	0.249	(0.027)	***
Turn	0.170	(0.016)	***	0.094	(0.017)	***	0.194	(0.021)	***
Age	0.168	(0.038)	***	-0.005	(0.040)		0.226	(0.050)	***
Region	-0.185	(0.037)	***	-0.279	(0.036)	***	-0.065	(0.048)	
Const	-3.628	(0.195)	***	-3.098	(0.198)	***	-5.265	(0.256)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	72198			72356			58824		
Chi^2	4979.14***			1532.32***			4486.35***		
Pseudo-R^2	.55424742			0.52063401			0.54867196		
Log-Likelihood	-31315.886			-26354.124			-22009.957		

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %
Source: IABB, 1996-2008. Own calculations.

Table 2.6: Correlations of the independent variables.

	Indlev	*Complev*	*Size*	*Turn*	*Region*	*Resdept*	*Age*	*Exp*	*Counc*
Indlev	1								
Complev	-0.233	1							
Size	0.332	0.166	1						
Turn	0.332	0.155	0.915	1					
Region	-0.226	0.059	0.161	-0.199	1				
Resdept	0.077	0.085	0.435	0.429	-0.058	1			
Age	-0.082	-0.020	-0.109	-0.123	-0.006	-0.024	1		
Exp	0.089	0.038	0.389	0.421	-0.139	0.458	-0.027	1	
Counc	0.327	0.205	0.681	0.680	-0.126	0.372	-0.079	0.328	1

Source: IABB, 1996-2008. Own calculations.

Table 2.7: Mean and standard deviation of the additional control variables.

Variables	N	Mean	Std. Dev.
Size	178783	3.3939	1.9245
Turn	121577	14.4732	2.2711
Age	205965	0.0784	0.2688
Exp	166220	6.4391	17.3951

Source: IABB, 1996-2008. Own calculations.

3 More flexibility for more innovation? Evidence from the Netherlands

This papers deals with labor market flexibility and its relationship with innovation. Using a unique Dutch dataset from 1998 to 2008 with comprehensive information from employers and employees, we examine numerical, functional and in particular financial aspects of labor market flexibility. In a Panel Probit model, we show that most of the indicators of financial flexibility have a positive correlation and vary by type of innovation. While the variables of wage bargaining have a stronger association with process innovations, information about specific wage levels are particularly correlated with the development of new products. Aspects of numerical and functional labor market flexibility, in contrast, have a negative relationship with all types of innovation. Thereby, part-time employees are particularly associated with process innovations, while flexible employment contracts have a stronger correlation with new products. It turns out that process innovations require more flexibility than product innovations, that depend more on the employment status and the resulting motivation of the employees.

3.1 Introduction

Labor market flexibility continues to be one of economics, politics and society highly debated topic. Especially after the sharp rise in unemployment in Europe in the 1970s and 1980s, many labor market economists claim for increasing labor market flexibility, in order to improve the adaptability and mobility of businesses and employees (Brodsky, 1994; OECD, 1994; Siebert, 1997). The impact of labor market flexibility on economic aspects has been discussed for a long time, especially with regard to employment, growth, profits or productivity.[1]

At the same time, the need for more security, especially since the recent financial crisis, continues to grow, reflected in the new concept of `flexicurity' by Wilthagen and Tros (2004). A company's success always depends on the motivation of its employees. Particularly cost intensive projects require the willingness of the employees to bear the risk of a company. Exactly this trade-off between flexibility and security as a working motivation concerns the generation of innovations. In recent years, the potential impact of labor market flexibility on research and innovation has gained more and more attention.

Existing studies on labor market flexibility and innovation focus on numerical and functional aspects and mostly show a negative correlation with innovation, although the data are often not on a sufficient company level (Freeman, 2005; Zhou et al., 2011).[2] Additionally, financial flexibility has hardly been explored in previous analysis (Zhou et al., 2011: 3). In addition, approaches of wage flexibility, as given by Sanchez and Toharia (2000), are mostly reduced to aspects of efficiency wages or the insider-outsider context. Pooling three datasets from the Netherlands, we obtain several measures of financial flexibility. Together with data on numerical and functional flexibility, we can characterize labor market flexibility much more comprehensive and find a significant correlation depending on the type of innovation.

1 For a survey of theoretical approaches see Towers (1992) or Solow (1998). A review of labor market flexibility, its definitions and implications can be found in e.g. Solow (1998), Beatson (1995) or Salvanes (1997).

2 Studies with data on company level are e.g. Arvanitis (2005), Michie and Sheehan (2003) or Kleinknecht et al. (2006).

The rest of the paper is structured as follows. In Chapter 3.2, we give a definition of labor market flexibility and its elements. The following Chapter 3.3 introduces possible effects of labor market flexibility on innovation and provides a short survey of previous studies. The available data is summarized in Chapter 3.4. After a description of the empirical model in Chapter 3.5, the results are presented in the subsequent Chapter 3.6. Finally, Chapter 3.7 summarizes some conclusions.

3.2 Labor market flexibility

Labor market flexibility represents the capacity of the labor market to adapt quickly to changes in economy or society. The most commonly used definition is given by Atkinson (1985).[3] He defines labor market flexibility as a function of corporate strategy and divides it in three different groups: the numerical, functional and financial. In addition, external and internal aspects of flexibility can be distinguished.

External numerical flexibility refers to the mobility of employees between different companies by terminations and new recruitments. Thereby, it illustrates the extent to which the number of employees can be adapted quickly to economic requirements. Options of external numerical flexibility are flexible employment contracts such as part-time or temporary employment. These forms of employment facilitate a faster change of the number of employees. Internal numerical flexibility refers to the ability of a company to adjust the working hours of its employees. It can affect daily, weekly or annual working time as well as seasonal arrangements or short-time work.

Functional flexibility describes how a company can use its employees for different tasks. Internal functional flexibility includes continued training so that multi-skilled employees are able to fulfill a variety of tasks. In addition, an external solution is possible by outsourcing or temporary employment.

[3] Further classifications of labor market flexibility can be found in e.g. Beatson (1995), Klau and Mittelstädt (1986) or Blyton (1992).

Financial flexibility can be defined as the flexibility of wages and is represented particularly by decentralized wage bargaining. In this way, wages represent the equilibrium supply and demand on the labor market.

Flexible labor contracts such as part-time employment and temporary employment contracts are often labeled as atypical work. In selected sectors and especially for certain groups of employees, such as for example low-skilled employees or women, atypical work is now common practice (Grip et al., 1997; O'Reilly and Fagan, 2002). Following the data from the OECD (2010), the share of temporary employment increased from 1994 to 2010 on average across all OECD countries. However, the results vary greatly depending on the considered country. In most countries, the share of temporary employment contracts is significantly higher or even twice as high for women and especially for young people aged between 15 and 24 (OECD, 2010: 288). The same applies to part-time contracts. In most of all countries, more than 70 percent of all part-time positions are filled by women, because they use part-time contracts frequently for re-entering the labor market after childbirth (OECD, 2010: 286).

3.3 Literature review

In recent years, the interest in the relationship between innovation and flexibility has increased and several studies have emerged with data from different countries, such as Italy (Pieroni and Pompei, 2008), Spain (Altuzarra and Serrano, 2010) or the Netherlands (Zhou et al., 2011). A survey of previous studies can be found in Storey (2001). Thereby, most of all studies focus on numerical and functional aspects of labor market flexibility.

Theoretically, numerical and functional labor market flexibility can be either negatively or positively associated with innovation. In general, it is assumed that the negative effects outweigh the positive effects based on the assumption that innovation is path dependent. That means that the implementation of new processes or products depends on aspects of the social environment, company culture, earlier investments as well as accumulated previous knowledge (Pavitt, 1991). Researchers such as Grant (1991) assume that the capabilities of an organization cannot be completely exhausted using short-term, temporary and part-time employment contracts. Following Zhou et al. (2011), temporary employment contracts undermine the training investments of a company. The knowledge and the productivity of the employees are migrating to another company. In this way, a company loses its competitive advantages. In addition, employees are only willing to take the risk of an innovation, when they get a sense of security in their employment (Storey et al., 2002: 1).

In contrast, arguments for a positive relationship between flexible employment contracts and innovation can also be found. Following the approaches of Kodama (1995) or Matusik and Hill (1998), not necessarily only internal resources are used for innovation. Instead, innovations depend much more on the effective utilization of technology and knowledge, even beyond internal capacities. According to Teece (1986: 288-289), the use of external capacities can be seen as additional innovation input factors, especially in the case of open source projects. In addition, Arvanitis (2005) argues that temporary employment contracts facilitate the adjustment to changing demand conditions. Following Adams and Brock (2004), flexible employment also allows a larger labor turnover, which introduces new knowledge and fresh ideas into a company and inefficient workers can easier be replaced (Zhou et al., 2011: 4). As Bassanini and Ernst (2002) or Scarpetta and Tressel (2004) emphasized, severe restrictions on terminations may also limit the incentive to implement labor-saving innovations. Finally, Ichniowski and Shaw (1995) think that permanent employees may be disinclined to change in form of innovation due to habit or so called lock-in effects.[4] In this respect, flexible working arrangements such as outsourcing, temporary or fixed-term contracts can fit exactly right with the innovation process.[5]

According to the different theoretical arguments, the results of previous empirical studies are not unambiguous. Michie and Sheehan (2003) use a large number of indicators to measure numerical and functional flexibility as well as the labor turn-

4 Although Zhou et al. (2011) argue that potential lock-in effects could be reduced by training and human resource policies. Further details can be found in Zhou et al. (2011: 4).

5 A survey of different theoretical approaches is given by Storey et al. (2002: 3-4), Pieroni and Pompei (2008: 326-329) or Zhou et al. (2011: 3-6) .

over. Their results show a significantly negative association of numerical flexibility measured by flexible and part-time employment contracts. Training and group work as indicators for functional flexibility, in contrast, are positively correlated with innovation. A summary of individual aspects makes clear that combinations of various flexibility measures also act differently (Michie and Sheehan, 2003: 132-133). An increased flexibility seems to have a positive effect up to a certain limit. Zhou et al. (2011) also present a positive relationship between variables measuring internal functional flexibility and the turnover of new products. At the same time, temporary employment contracts are also positively correlated. The results of Pieroni and Pompei (2008) clarify a significantly negative correlation between labor turnover and patents. A more qualitative evaluation approach is chosen by Storey et al. (2002). They show that the employees directly involved in the innovation process are much less affected by flexible working arrangements. Temporary or fixed-term contracts are used primarily for cost reduction. However, the companies that complete many of these flexible contracts prove to be highly innovative. Storey et al. (2002) suggest that flexible employees support the innovators. Therefore, they do not affect innovations directly, but rather reflect the innovation activities of a company (Storey et al., 2002: 11).

The impact of financial flexibility, especially in the combination with numerical and functional flexibility, is studied very little, which is mostly based on the lack of equivalent data (Zhou et al., 2011: 3). Financial flexibility refers to two aspects. The first one is the way of wage-setting. Following the current innovation literature, mostly a negative relationship is assumed.[6] Based on the hold-up effect, as established by Grout (1984), a union acts like a tax on intangible capital returns in order to get a share of quasi-rents (Hirsch and Connolly, 1987). Following this so-called rent-seeking approach, the anticipation of the hold-up situation decreases the incentives to invest in innovation. Accordingly, the following hypothesis can be derived.

Hypothesis I A high degree of financial flexibility measured by decentralized wage-setting has a positive influence on innovation.

[6] A theoretical and empirical survey can be found in Menezes-Filho and Van Reenen (2003).

The second aspect of financial labor market flexibility refers to the wage level. Since several years, economists have often called to decrease wages in order to reduce the unemployment (OECD, 1994). However, Kleinknecht (1998) shows that decreasing wages with an associated increase in labor demand and a decline in unemployment can also be attributed to a low growth in labor productivity. From an innovation-economic perspective, a company with low labor costs has only a limited incentive to replace old by new capital (Kleinknecht, 1998: 389, 391). In addition, a restriction of wage increases also leads to a prevention of creative destruction, the core of the Schumpeterian theory. Following Schumpeter (1976), only strong and innovative companies will survive. Due to the possibility of higher monopoly profits as a result of a successfully implemented innovation, the innovator has an advantage over non-innovators in higher wage demands and a higher chance of survival. Therefore, the effect of wage levels does not seem to be unambiguous. Arguments for either a positive or a negative effect on innovation can be found. Lower wages allow a company to invest more financial resources in research and development (R&D), whereas higher wages can be viewed as an incentive for innovative effort. The direction of the effect depends ultimately on the costs and the target of the planned innovation, so that a second hypothesis can be established.

Hypothesis II The impact of financial flexibility measured by wage levels differs depending on the type of innovation.

The data as well as the empirical model to test these hypotheses are described in the following chapters.

3.4 Data

The dataset is a combination of three different data from the Netherlands. On the one hand, we use two datasets from the Centraal Bureau voor de Statistiek (CBS), the Central Bureau of Statistics of the Netherlands in The Hague. First, we use the Community Innovation Survey (CIS) of the European Commission with a standardized questionnaire for all participating European countries. In this way, it offers harmonized information on research and innovation such as R&D expenditures, incentives as well as barriers to innovate using the official definitions of the Oslo Manual of the OECD (2005). Second, data of the Dutch income tax office are used. This employee's level dataset contains extensive information about employment contracts such as working hours or wages. Furthermore, data on the employees themselves such as gender or age are included. An identification number allows the assignment of employees to a company. Entry and exit data indicate the duration of employment of an individual employee in a specific company within a respective year. In addition, they illustrate the employment changes within an organization.[7] The variable Collective Labour Agreement (CAO), assigned by the negotiating union, shows for each employee whether its salary was negotiated collectively. The number identifies a specific collective agreement, if one has been completed. However, there is no information on wehether this agreement was negotiated at company or at industry level.

On the other hand, we use the Dutch Collective Labour Agreements Database and Monitor (DUCADAM) of the Amsterdam Institute for Advanced Labour Studies (AIAS), an independent research institute of the University of Amsterdam. This data collection contains all collective labor agreements (CLAs) in the Netherlands, resulting from an extensive inquiry as well as a co-operation with the Federatie Nederlandse Vakbeweging (FNV), the Dutch Trade Union Confederation. In addition to the CAO number, the dataset also includes relevant company and bargaining variables, such as the level of the bargaining process.[8] The CAO number is used to match the DUCADAM data with the wage dataset from the CBS. Aggregated on company level, we match this dataset with the CIS data using the company's identification number. In this way, information about research and innovation could be associated with labor market data. Due to the fact that the CIS data does not contain information about the public sector, we excluded all observations of the public sector in the wage dataset.

7 Thereby, the entrance month is counted only if the employment has started not later than the 15th day of the month. On the other side, the leaving month is counted only if the employment has determined after the 15th day of the month.

8 Further information about the DUCADAM dataset can be found in Hartog et al. (1999). Details about the variables and their encoding are given in Schreuder and Tijdens (2004).

The whole dataset contains data for every second year from 1998 until 2008. With approximately 9,000 surveyed companies per year, the whole dataset covers about 50,000 observations. All monetary variables are given in Euro (€).

Table 3.1 summarizes some descriptive statistics. More than 36 percent of all observations are innovators. Thereby, product innovations are more common than process innovations. The real estate and investment goods as well as the wholesale and retail are the most common sectors. More than 50 percent of all companies belong to services sectors, while most of the innovators and especially of the product innovators are manufacturing companies. Most of all observations are small companies with less than 50 employees. Only about ten percent have 200 or more employees. However, innovating companies are significantly larger. The share of companies that are doing research regularly is about thirteen percent for all observation and more than 35 percent for innovators.

With more than 85 percent, most of all observations pay a collectively bargained wage. Thereby, most of the companies pay a wage that is collectively bargained at industry level. The share of agreements at company level is about seven percent and increasing over time. However, innovators choose more often an agreement at company level.

About 60 percent of the employees within a company are working on full-time and only less than 40 percent on part-time. The share of full-time employees is even higher for companies with a successful innovation. Most of all employees have a fixed contract. About 75 percent of the employees in all companies and up to 80 percent of the employees in innovating companies have a permanent working contract.

Table 3.1: Summary of descriptive statistics, percentage.

	All	Innovators	Processes	Products
Innovation	36.59			
Process innovation	21.58			
Product innovation	27.79			
Sectors				
Agriculture	2.17	2.17	1.93	2.53
Nutrition	4.29	4.82	4.99	6.32
Consumer goods	1.40	1.30	1.90	2.39
Publishing industry	4.18	4.39	4.08	6.05
Producer goods	9.41	12.43	12.58	14.35
Machine construction	5.12	12.60	14.15	13.58
Investment goods	16.69	13.52	13.87	14.96
Wholesale	10.82	12.69	12.40	9.83
Retail	12.45	5.66	4.68	4.34
Transportation	7.83	5.70	4.76	5.52
Business services	4.68	6.55	7.59	5.17
Real estate	18.59	15.89	15.31	12.90
Other services	2.39	1.77	1.77	2.05
Total	100.00	100.00	100.00	100.00
Employment size				
Less than 50	50.75	39.61	38.86	36.54
50-199	39.07	44.06	44.28	44.22
200 and more	10.18	16.33	16.86	19.25
Total	100.00	100.00	100.00	100.00
Research				
Non-researching companies	87.63	68.70	64.88	62.12
Researching companies	12.37	31.30	35.12	37.88
Total	100.00	100.00	100.00	100.00
Collective bargaining				
Bargaining at industry level	86.11	82.71	81.78	81.91
Bargaining at company level	6.12	9.58	11.08	10.14
No collective bargaining	7.77	7.70	7.13	7.95
Total	100.00	100.00	100.00	100.00
Labor market flexibility				
Part-time employees	36.42	30.06	29.38	29.03
Flexible contract	6.58	3.20	3.24	2.83
Temporary contract	24.45	21.04	20.60	20.75
Permanent contract	75.55	78.96	79.4	79.25

Source: CBS, AIAS 1998 - 2008, own calculations.

3.5 Empirical model

As the dependent variable, we use the binary-coded variable *Inno*, which identifies companies with a successful innovation. Due to the binary coding of the dependent variables, we use a Random Effects Panel Probit model. It can be written as

$$Prob(\textit{Inno}=1 \mid X) = \Phi\,(X'\beta) + \varepsilon, \tag{1}$$

with X as a vector of independent variables and Φ as the Cumulative Distribution Function of the standard normal distribution. It can be interpreted as the probability of a company to be an innovator given the variables summarized in X. The vector X contains information on labor market flexibility and additional control variables. The financial flexibility is measured by variables describing the bargaining process as well as the wage level. The grouped variable *Bargainlev* specifies the level of wage bargaining. The higher the value of *Bargainlev,* the more likely the transaction takes place at a decentralized level. The lowest value is the inflexible wage-setting at industry level. In contrast, a fully flexible wage-setting includes no collective bargaining. *Bargaincov* indicates the percentage of employees in a company which is subject to the collectively agreed wages. Variables describing the amount of wages are *Medwage* as the average wage and *Diffwage* as the wage differential within a company. According to our first hypothesis, we expect a positive correlation of the variable *Bargainlev* with innovation. Following our second hypothesis, the variables *Medwage* and *Diffwage* will depend on the type of innovation.

Numerical and functional flexibility is measured by five variables.[9] *Parttime* is the share of part-time employees, while *Employstat* indicates the share of workers with a flexible employment status. In addition to temporary employees, it also includes on-demand workers. The share of workers with a temporary employment contract is represented by the variable *Tempemp*. To indicate changes in employment and the flexible adjustment of the number of employees within a company, we include the labor turnover. Based on Zhou et al. (2011: 8), the labor turnover *Labturn* is given by the share of employees that left the company within a year.

[9] Due to the fact that no information about training or further education can be found in the dataset, we put together internal and external components.

The control variables include the company's *Size*, measured by the logged number of employees, and the logarithm of the annual turnover *Turn*. The variable refers to the turnover of the previous period, which reduces potential endogeneity problems. The binary coded variable *Research* controls for existing research activities of a company. *Holland* identifies companies with headquarters in the Netherlands and is used to measure activities in foreign markets. The variable *Group* refers to companies that are part of a corporate group. The firm's *age* is approximately given by the age of employees within a company.[10] In addition, the individual dummies *Sec* and *Year* for industries and years are included.

Given the described variables, the following equation (2) is obtained

$$Prob(\textit{Inno}=1|X) = \Phi\,(\beta_0 + \beta_1 \cdot \textit{Bargainlev} + \beta_2 \cdot \textit{Bargaincov} + \beta_3 \cdot \textit{Medwage} + \beta_4 \cdot \textit{Diffwage} + \beta_5 \cdot \textit{Parttime} + \beta_6 \cdot \textit{Employstat} + \beta_7 \cdot \textit{Tempemp} + \beta_8 \cdot \textit{Labturn} + \beta_9 \cdot \textit{Size} + \beta_{10} \cdot \textit{Turn} + \beta_{11} \cdot \textit{Research} + \beta_{12} \cdot \textit{Holland} + \beta_{13} \cdot \textit{Group} + \beta_{14} \cdot \textit{Age} + \beta_{15} \cdot \textit{Sec} + \beta_{16} \cdot \textit{Year}) \quad (2)$$

Following the model of Haucap and Wey (2004), the relationship between the level of wage bargaining and the incentive to innovate is not linear. Their model shows that coordinated bargaining at company level gives the lowest and centralized wage-setting at industry level the highest incentives to invest in cost-reducing process innovations. To take into account for a potential non-linearity, we use individual wage-setting levels in the regression in a further step. Using the most centralized bargaining at industry level *Indlev* as reference category, *Nolev* identifies companies without collective bargaining agreements, whereas *Complev* indicates companies with a wage-setting at company level.

$$Prob(\textit{Inno}=1|X) = \Phi\,(\beta_0 + \beta_1 \cdot \textit{Nolev} + \beta_2 \cdot \textit{Complev} + \beta_3 \cdot \textit{Bargaincov} + \beta_4 \cdot \textit{Medwage} + \beta_5 \cdot \textit{Diffwage} + \beta_6 \cdot \textit{Parttime} + \beta_7 \cdot \textit{Employstat} + \beta_8 \cdot \textit{Tempemp} + \beta_9 \cdot \textit{Labturn} + \beta_{10} \cdot \textit{Size} + \beta_{11} \cdot \textit{Turn} + \beta_{12} \cdot \textit{Research} + \beta_{13} \cdot \textit{Holland} + \beta_{14} \cdot \textit{Group} + \beta_{15} \cdot \textit{Age} + \beta_{16} \cdot \textit{Sec} + \beta_{17} \cdot \textit{Year}) \quad (3)$$

In addition, we distinguish between process and product innovations using the variables *Proc* and *Prod* as dependent variables. Equation (2) and (3) are calculated

[10] Unfortunately, the dataset does not contain information about the age of a company. Following the results of Ouimet and Zarutskie (2011), the employee's age is strongly positively associated with the age of the company. See Ouimet and Zarutskie (2011: 1).

for *Inno*, *Proc* and *Prod* separately. Table 3.4 in the appendix summarizes the individual empirical regression equations and describes the variables used in each case.

3.6 Results

The results of the Panel Probit regression for equation (2) are presented in Table 3.2. The marginal effects are sorted by the different types of flexibility as well as the dependent variables *Inno*, *Proc* and *Prod*.[11] The relationship between the financial flexibility and *Inno* is mostly positive. However, some significant differences between the two types of innovation *Proc* and *Prod* can be found. The variables of wage bargaining are significantly higher correlated with *Proc*, while the information about the wage level is stronger associated with *Prod*.

The marginal effect of *Bargainlev* is highest for *Proc*. The more a wage is set on a flexible level, the higher the probability of process innovation. Therefore, our first hypothesis can be confirmed at least for process innovations. However, the correlation of *Bargainlev* with *Prod* is only about half as large and not significant. The same applies to the bargaining coverage *Bargaincov*. A high share of employees within a company, who are affected by the wage agreement, increases the probability of *Proc*, while the marginal effect for *Prod* is even slightly negative and repeatedly not significant. In contrast, the variable *Medwage* is positively and signifcantly correlated with all types of innovation, whereas the marginal effect for *Prod* is slightly higher. The same applies to the variable *Diffwage*. The marginal effect for *Prod* is again slightly higher. Due to these differences between the two types of innovation, our second hypothesis can also be confirmed.

[11] The difficulties in the calculation of the marginal effects are known, particularly when several binary coded explanatory variables are used. The resulting coefficients are listed in Table 3.5 and 3.6 in the appendix.

Table 3.2: Marginal effects of the Panel Probit regression equation (2).

	(2)								
	Inno			Proc			Prod		
Bargainlev	0.046	(0.018)	**	0.042	(0.012)	***	0.021	(0.014)	
Bargaincov	0.051	(0.041)		0.056	(0.028)	**	-0.012	(0.032)	
Medwage	-1.50e^{-04}	(8.00e^{-05})	*	-4.00e^{-04}	(6.00e^{-04})		-8.25e^{-04}	(6.00e^{-05})	
Diffwage	2.50e^{-05}	(1.00e^{-05})	***	1.26e^{-06}	(1.00e^{-06})	***	1.61e^{-05}	(1.00e^{-05})	***
Parttime	-0.113	(0.033)	***	-0.051	(0.024)	**	-0.043	(0.027)	
Employstat	-0.072	(0.043)	*	-0.017	(0.031)		-0.075	(0.035)	**
Tempemp	-0.029	(0.029)		-0.014	(0.020)		-0.047	(0.023)	**
Labturn	-0.111	(0.040)	***	-0.067	(0.028)	**	-0.055	(0.032)	*
Size	0.073	(0.006)	***	0.050	(0.004)	***	0.043	(0.015)	***
Turn	0.014	(0.004)	***	0.011	(0.003)	***	0.014	(0.004)	***
Service	-0.143	(0.028)	***	-0.072	(0.020)	***	-0.066	(0.022)	***
Research	0.684	(0.011)	***	0.358	(0.016)	***	0.657	(0.003)	***
Group	0.041	(0.012)	***	0.026	(0.008)	***	0.044	(0.009)	***
Holland	-0.042	(0.027)		-0.007	(0.017)		0.006	(0.019)	
Age	-0.011	(0.003)	***	-0.004	(0.002)	*	-0.009	(0.003)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi^2	2079.55***			1672.56***			2136.52***		
Pseudo-R^2	0.81037			0.81037			0.81037		
Log-Likelihood	-7762.3707			-7762.3707			-7762.3707		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

The variables of the numerical and functional labor market flexibility have a negative association with *Inno* as well as with *Prod* and *Proc*. Thereby, *Parttime* and *Labturn* are significantly higher negatively correlated with *Proc*, while *Employstat* and *Tempemp* have a significantly higher negative association with *Prod*.

The results of equation (3), including the individual bargaining levels, can be found in Table 3.3. Compared to centralized wage bargaining at industry level, *Nolev* and *Complev* are positively associated with *Inno*. Thereby, *Nolev* has the highest positive marginal effect. The assumed non-linearity, as stated by Haucap and Wey (2004), cannot be found in our estimations. In addition, the marginal effects and significance levels of *Nolev* and *Complev* are significantly higher for *Proc* than for *Prod*.

Table 3.3: Marginal effects of the Panel Probit regression, equation (3).

	(3)								
	Inno			Proc			Prod		
Nolev	0.070	(0.050)		0.084	(0.040)	**	0.031	(0.041)	
Complev	0.061	(0.026)	**	0.049	(0.018)	***	0.028	(0.020)	
Indlev	--	--		--	--		--	--	
Bargaincov	0.028	(0.051)		0.051	(0.036)		-0.024	(0.040)	
Medwage	$-1.55e^{-04}$	$(8.00e^{-05})$	**	$-4.03e^{-05}$	$(6.00e^{-05})$		$-8.30e^{-05}$	$(6.00e^{-05})$	
Diffwage	$2.50e^{-05}$	$(1.00e^{-05})$	***	$1.25e^{-05}$	$(1.00e^{-05})$	***	$1.59e^{-05}$	$(1.00e^{-05})$	***
Parttime	-0.113	(0.033)	***	-0.051	(0.024)	**	-0.043	(0.027)	
Employstat	-0.072	(0.043)	*	-0.016	(0.031)		-0.074	(0.035)	**
Tempemp	-0.029	(0.029)		-0.014	(0.020)		-0.047	(0.023)	**
Labturn	-0.111	(0.040)	***	-0.067	(0.028)	**	-0.055	(0.078)	*
Size	0.072	(0.006)	***	0.050	(0.004)	***	0.043	(0.004)	***
Turn	0.014	(0.004)	***	0.011	(0.003)	***	0.014	(0.003)	***
Service	-0.143	(0.028)	***	-0.073	(0.020)	***	-0.066	(0.022)	***
Research	0.684	(0.011)	***	0.358	(0.016)	***	0.657	(0.015)	***
Group	0.041	(0.012)	***	0.026	(0.008)	***	0.044	(0.009)	***
Holland	-0.042	(0.027)		-0.006	(0.017)		0.001	(0.019)	
Age	-0.010	(0.003)	***	-0.004	(0.002)	*	-0.009	(0.003)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi²	2079.11***			1672.47***			2135.97***		
Pseudo-R^2	0.810378			0.813503			0.837974		
Log-Likelihood	-7762.0902			-7634.1916			-6632.4634		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

The marginal effects and significance level of the other variables of financial flexibility change only slightly in equation (3). The association of the wage bargaining variables with *Proc* is still the strongest. The variables relating to the wage level are still more associated with *Prod*, so that our second hypothesis is further confirmed.

The control variables in equation (2) and (3) remain relatively constant. The *Size* is positively associated, while the *Age* is rather negatively correlated with all types of innovation. *Turn* and *Research* significantly increase the probability of successful innovations. Thereby, the development of *Prod* depends much more on research and investments. The marginal effects of *Holland* vary and are not significant. The variable *Group* is positively correlated with *Inno*, whereas the marginal effect is about twice as high as for *Prod* than for *Proc*. The results of the regressions show that innovations are most likely in large and younger companies that conduct research on a regular basis. Regarding the flexibility variables, process innovations are likely in companies with more full-time workers, who choose for the largest share of their employees a more decentralized wage-setting. Companies with product innovations, in contrast, are characterized by a high share of employees with a fixed and permanent contract, with a lower wage level as well as by a high number of new entries. The results suggest a possible higher significance of the employee's working motivation towards the development of product innovations, while process innovations seem to depend rather on working hours.

The analysis of labor market flexibility and innovation always induces potential problems with endogeneity. The mentioned arguments about the relationship between aspects of labor market flexibility and innovation can also be reversed. The wage-setting or the wage levels as well as the number of flexible employment contracts may also be influenced by the generation of innovations, as shown by Storey et al. (2002). Their results demonstrate that flexible working contracts are often a consequence of innovation (Storey et al., 2002: 1). Michie and Sheehan (1999: 221-222) also refer to a possible reverse causality. In addition, they also point to a simultaneous incidence of technological changes and changes in the organizational structure of work, which is particularly related to the variables of numerical and functional labor market flexibility. Due to the lack of suitable instrumental variables for all individual aspects of labor market flexibility, we have tested the results using lagged values of the variables without finding significant differences.[12] However, it is important to note that the resulting correlations do not necessarily reflect a one-way causality.

[12] The results are listed in Table 3.7 and 3.8 in the appendix. Additonally, a correlation matrix of the independent variables as well as additonal descriptive statistics can be found in Table 3.9 and 3.10.

3.7 Conclusions

In this paper, we analyze the relationship between labor market flexibility and innovation. We find out that financial flexibility as a part of labor market flexibility indeed is correlated with the probability to innovate. However, the relationship depends on the variables used to measure financial flexibility and on the type of innovation. Information about the wage bargaining are positively associated with process innovations, while variables considering the actual wage level are more negatively correlated with new products. A flexible wage bargaining with a high bargaining coverage increases the probability of process innovation. In contrast, a high wage differential within a company with a low average wage supports the generation of product innovations

Financial flexibility particularly refers to the cost side of a company. Process innovations are mostly targeted on a cost reduction. Thus, the more flexible the financial statements of a company, the easier it seems to implement a successful cost-reducing process innovation. Thereby, the opportunity to change the ongoing labor costs is primarily important. The same is true for numerical and functional aspects of labor market flexibility. Part-time employment decreases the probability of process innovation, while flexible and non-permanent contracts are only slightly and not significantly correlated. That means, flexible contract terminations as well as flexible wage-setting are important for cost-reducing process innovations.

In contrast, the development of new products seems to depend much more on the wage level and the contract form and their impacts on the motivation of the employees. A product innovation usually needs more financial resources and involves a higher risk for the company as well as for its employees, reflected in the marginal effects of the variables *Turn* and *Research* in our regression results in Table 3.2 and Table 3.3. To make its employees able to take the risk of a product innovation, a company has to give them an incentive, such as a higher wage. The regression results show that the higher the wage differential within a company, the higher the probability of product innovations. Hence, the wage differential could be an incentive for an employee to make its contribution to the development of a new product. In addition, the incentive also concerns labor security. Flexible employment and non-permanent contracts reduce the probability of a new product up to three times more than they reduce the incentive for process innovations.

Our results illustrate that the relationship between labor market flexibility and innovation activities strongly depends on the type of innovation. While process innovations require a more flexible wage-setting process, the development of new products, in contrast, depends much more on incentives such as a higher labor security. In order to further look into the relationship between different aspects of labor market flexibility and innovation, we think that future research should focus on two points. On the one hand, potential repercussion effects of innovations should be examined more closely in future studies, considering the impact of innovation activities on the choice of labor contracts in the future. On the other hand, the detailed contribution to the innovation process of employees who are working on a flexible part-time or temporary contract should be investigated. Following Torka et al. (2011), the participation of these employees and their quality should be given more attention, which also requires qualitative research.

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Appendix

Table 3.4: Description of included variables and regression models.

Variables	Description	Code	(2)	(3)
Dependent variables				
Inno	Innovator	Binary	x	x
Process	Process innovator	Binary	x	x
Product	Product innovator	Binary	x	x
Financial flexibility				
Bargainlev	Wage bargaining level	Grouped 1-3	x	x
Bargaincov	Share of employees with collective wages	Percentage	x	x
Nolev	No collective bargaining	Binary		x
Complev	Collective bargaining at company level	Binary		x
Indlev	Collective bargaining at industry level	Binary		
Medwage	Median monthly wage per employee	Continuous	x	x
Diffwage	Wage differential within a company	Continuous	x	x
Numerical, functional flexibility				
Parttime	Share of part-time employees	Percentage	x	x
Employstat	Share of employees with flexible contract	Percentage	x	x
Tempemp	Share of employees with temporary contract	Percentage	x	x
Labturn	Share of employees who left within a year	Percentage	x	x
Control variables				
Size	Logarithm of the number of employees	Continuous	x	x
Turn	Logarithm of the previous annual turnover	Continuous	x	x
Research	Company is doing research	Binary	x	x
Holland	Headquarter is in the Netherlands	Binary	x	x
Group	Company is part of a group of companies	Binary	x	x
Age	Age of the employees within a company	Continuous	x	x
Sec	Sectors dummies	Binary	x	x
Year	Year dummies	Binary	x	x

Table 3.5: Coefficients of the Panel Probit regression equation (2).

	(2)								
	INNO			PROC			PROD		
BARGAINLEV	0.124	(0.048)	**	0.159	(0.045)	***	0.078	(0.051)	
BARGAINCOV	0.136	(0.111)		0.222	(0.106)	**	-0.045	(0.118)	
MEDWAGE	$-4.13e^{-04}$	$(2.11e^{-04})$	*	$-1.51e^{-04}$	$(2.23e^{-04})$		$-3.09e^{-04}$	$(2.28e^{-04})$	
DIFFWAGE	$6.83e^{-05}$	$(1.81e^{-05})$	***	$4.76e^{-05}$	$(1.64e^{-05})$	***	$6.02e^{-05}$	$(1.86e^{-05})$	***
PARTTIME	-0.304	(0.089)	***	-0.192	(0.089)	**	-0.159	(0.099)	
EMPLOYSTAT	-0.194	(0.115)	*	-0.063	(0.116)		-0.280	(0.133)	**
TEMPEMP	-0.078	(0.078)		-0.051	(0.076)		-0.174	(0.086)	**
LABTURN	-0.298	(0.108)	***	-0.255	(0.108)	**	-0.207	(0.118)	*
SIZE	0.195	(0.015)	***	0.189	(0.014)	***	0.163	(0.016)	***
TURN	0.038	(0.012)	***	0.043	(0.012)	***	0.051	(0.013)	***
SERVICE	-0.385	(0.075)	***	-0.274	(0.075)	***	-0.246	(0.081)	***
RESEARCH	2.134	(0.063)	***	1.075	(0.043)	***	1.947	(0.054)	***
GROUP	0.110	(0.032)	***	0.098	(0.032)	***	0.169	(0.035)	***
HOLLAND	-0.111	(0.072)		-0.024	(0.064)		0.002	(0.072)	
AGE	-0.028	(0.009)	***	-0.017	(0.009)	*	-0.035	(0.010)	***
CONSTANT	-0.785	(0.279)	***	-1.478	(0.280)	***	-1.406	(0.306)	***
SEC	Yes			Yes			Yes		
YEAR	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi^2	2079.55***			1672.56***			2136.52***		
Pseudo-R^2	.81037			.81037			.81037		
L-Likelihood	-7762.3707			-7762.3707			-7762.3707		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

Table 3.6: Coefficients of the Panel Probit regression, equation (3).

	(3)								
	Inno			Proc			Prod		
Nolev	0.184	(0.128)		0.287	(0.125)	**	0.110	(0.141)	
Complev	0.159	(0.067)	**	0.173	(0.061)	***	0.101	(0.069)	
Bargaincov	0.076	(0.137)		0.194	(0.134)		-0.090	(0.150)	
Medwage	$-4.15e^{-04}$	$(2.11e^{-04})$	**	$-1.52e^{-04}$	$(2.23e^{-04})$		$-3.11e^{-04}$	$(2.29e^{-04})$	
Diffwage	$6.72e^{-05}$	$(1.81e^{-05})$	***	$4.71e^{-05}$	$(1.64e^{-05})$	***	$5.94e^{-05}$	$(1.87e^{-05})$	***
Parttime	-0.303	(0.089)	***	-0.192	(0.089)	**	-0.159	(0.099)	
Employstat	-0.193	(0.115)	*	-0.062	(0.116)		-0.278	(0.133)	**
Tempemp	-0.079	(0.078)		-0.052	(0.076)		-0.175	(0.086)	**
Labturn	-0.298	(0.108)	***	-0.254	(0.108)	**	-0.207	(0.118)	*
Size	0.194	(0.015)	***	0.188	(0.015)	***	0.162	(0.016)	***
Turn	0.038	(0.012)	***	0.043	(0.012)	***	0.051	(0.013)	***
Service	-0.385	(0.075)	***	-0.274	(0.075)	***	-0.246	(0.081)	***
Research	2.133	(0.063)	***	1.074	(0.043)	***	1.947	(0.054)	***
Group	0.110	(0.032)	***	0.098	(0.032)	***	0.169	(0.035)	***
Holland	-0.110	(0.072)		-0.024	(0.064)		0.003	(0.072)	
Age	-0.028	(0.009)	***	-0.016	(0.009)	*	-0.035	(0.010)	***
Constant	-0.720	(0.292)	**	-1.447	(0.293)	***	-1.358	(0.322)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi^2	2079.11***			1672.47***			2135.97***		
Pseudo-R^2	.810378			.813503			.837974		
L-Likelihood	-7762.0902			-7634.1916			-6632.4634		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

Table 3.7: Coefficients of the Panel Probit regression equation (2) using the lagges values of labor market flexibility.

	(2)								
	Inno			Proc			Prod		
$Bargainlev_{t-2}$	0.122	(0.048)	**	0.157	(0.045)	***	0.075	(0.051)	
$Bargaincov_{t-2}$	0.130	(0.111)		0.217	(0.106)	**	-0.055	(0.118)	
$Medwage_{t-2}$	$-4.2e^{-04}$	$(2.1e^{-04})$	**	$-1.5e^{-04}$	$(2.2e^{-04})$		$-3.0e^{-04}$	$(2.3e^{-04})$	
$Diffwage_{t-2}$	$7.0e^{-05}$	$(1.8e^{-05})$	***	$4.8e^{-05}$	$(1.6e^{-05})$	***	$6.0e^{-05}$	$(1.9e^{-05})$	***
$Parttime_{t-2}$	-0.269	(0.088)	***	-0.165	(0.088)	*	-0.116	(0.098)	
$Employstat_{t-2}$	-0.173	(0.115)	*	-0.018	(0.114)		-0.205	(0.130)	
$Tempemp_{t-2}$	-0.070	(0.078)	***	-0.012	(0.074)		-0.111	(0.083)	
$Labturn_{t-2}$	-0.237	(0.108)	***	-0.250	(0.108)	**	-0.207	(0.118)	*
Size	0.194	(0.015)	***	0.188	(0.014)	***	0.162	(0.016)	***
Turn	0.038	(0.012)	***	0.043	(0.012)	***	0.051	(0.013)	***
Research	2.134	(0.063)	***	1.075	(0.043)	***	1.947	(0.054)	***
Group	0.113	(0.032)	***	0.100	(0.032)	***	0.173	(0.035)	***
Holland	-0.111	(0.072)		-0.024	(0.064)		0.003	(0.072)	
Age	-0.688	(0.153)	***	-0.777	(0.152)	***	-0.683	(0.168)	
Constant	-0.760	(0.279)	***	-1.460	(0.279)	***	-1.382	(0.306)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi^2	2076.18***			1670.71***			2133.71***		
L-Likelihood	-7765.7111			-7636.3525			-6636.9434		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

Table 3.8: Coefficients of the Panel Probit regression equation (3) using the lagges values of labor market flexibility.

	(3)								
	Inno			Proc			Prod		
Complev_{t-2}	0.122	(0.128)		0.282	(0.125)	**	0.100	(0.141)	
Nolev_{t-2}	0.159	(0.067)	**	0.172	(0.061)	***	0.099	(0.069)	
Bargaincov_{t-2}	0.067	(0.137)		0.186	(0.134)		-0.103	(0.150)	
Medwage_{t-2}	$-4.2e^{-04}$	$(2.1e^{-04})$	**	$-1.5e^{-04}$	$(2.2e^{-04})$		$-3.0e^{-04}$	$(2.3e^{-04})$	
Diffwage_{t-2}	$6.8e^{-05}$	$(1.8e^{-05})$	***	$4.8e^{-05}$	$(1.6e^{-05})$	***	$6.1e^{-05}$	$(1.9e^{-05})$	***
Parttime_{t-2}	-0.269	(0.088)	***	-0.165	(0.088)	*	-0.116	(0.098)	
Employstat_{t-2}	-0.135	(0.113)		-0.018	(0.114)		-0.204	(0.130)	
Tempemp_{t-2}	-0.027	(0.075)		-0.012	(0.074)		-0.112	(0.083)	
Labturn_{t-2}	-0.002	(0.001)	**	-0.002	(0.001)	*	-0.001	(0.001)	
Size	0.193	(0.015)	***	0.188	(0.014)	***	0.161	(0.016)	***
Turn	0.038	(0.012)	***	0.043	(0.012)	***	0.051	(0.013)	***
Research	2.133	(0.063)	***	1.074	(0.043)	***	1.946	(0.054)	***
Group	0.112	(0.032)	***	0.100	(0.032)	***	0.172	(0.035)	***
Holland	-0.110	(0.072)		-0.024	(0.064)		0.003	(0.072)	
Age	-0.805	(0.153)	***	-0.780	(0.153)	***	-0.688	(0.169)	***
Constant	-0.694	(0.009)	**	-1.426	(0.293)	***	-1.329	(0.322)	***
Sec	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
N	16444			16444			16444		
Wald-Chi^2	2076.22***			1670.62***			2133.14***		
L-Likelihood	-7765.7234			-7636.2831			-6636.8074		

Notes: Standard errors in parentheses. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: CBS, AIAS 1998 - 2008, own calculations.

Table 3.9: Correlations of the independent variables.

	Bargainlev	Bargaincov	Diffwage	Research	Turn	Size	Holland	Group	Parttime	Employstat	Tempemp	Labturn	Age
Bargainlev	1												
Bargaincov	-0.751	1											
Diffwage	0.124	-0.087	1										
Research	0.058	0.026	0.150	1									
Turn	0.050	-0.017	0.166	0.101	1								
Size	0.025	0.077	0.093	0.208	0.003	1							
Holland	-0.066	0.012	-0.075	-0.112	-0.033	-0.122	1						
Group	0.046	0.001	0.102	0.141	0.145	0.238	-0.181	1					
Parttime	-0.053	0.031	-0.164	-0.222	-0.264	-0.021	0.104	-0.194	1				
Employstat	-0.068	0.050	-0.080	-0.102	-0.068	-0.041	0.037	-0.049	0.402	1			
Tempemp	-0.060	0.024	-0.071	-0.096	-0.116	0.026	0.033	-0.044	0.370	0.427	1		
Labturn	-0.016	-0.031	-0.066	-0.148	-0.117	-0.067	0.052	-0.076	0.422	0.406	0.333	1	
Age	0.004	0.022	0.041	0.029	-0.001	-0.001	-0.004	0.009	-0.224	-0.184	-0.295	-0.195	1

Source: CBS, AIAS 1998 - 2008, own calculations.

Table 3.10: Mean and standard deviation of the additional control variables.

Variable	Inno			Proc			Prod		
	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
Bargainlev	12687	0.2499	0.5844	7849	0.2535	0.5762	9309	0.2604	0.5930
Bargaincov	12687	0.1105	0.3213	7849	0.1270	0.3407	9309	0.1161	0.3277
Diffwage	19178	1334.02	1219.47	11281	1348.40	1344.17	14327	1369.23	1326.33
Medwage	19314	85.6621	355.9615	11336	73.0499	313.2457	14441	86.7309	359.4425
Turn	24281	5.0305	1.2513	13649	5.0728	1.2131	18198	5.0367	1.2261
Size	24319	4.2125	1.4346	13674	4.3545	1.4328	18218	4.2419	1.4496
Holland	24330	0.9419	0.2340	13680	0.9317	0.2524	18224	0.9385	0.2403
Group	24330	0.6585	0.4742	13680	0.6671	0.4713	18224	0.6746	0.4685
Labturn	19316	0.1945	0.1757	11338	0.1904	0.1726	14442	0.1894	0.1732
Age	19316	0.1891	0.1323	11338	0.1895	0.1261	14442	0.1884	0.1321

Source: CBS, AIAS 1998 - 2008, own calculations.

4 Innovative human resource management
The more the merrier?

This paper focuses on the empirical analysis of human resource management (HRM) practices and their association with innovation using a business survey of Australian companies from 2001 to 2010. It is investigated whether it is better to adopt as many practices as possible or whether individual HRM practices are particularly relevant. The human resources are involved in the entire innovation process and are therefore increasingly recognized as an important element for innovation. However, the interaction of HRM practices and innovation is barely considered in both, the HRM and the innovation literature. The results of an Ordered Probit regression show a significantly positive correlation between HRM practices and innovation activities, especially for practices related to payment and communication. Thereby, HRM practices are especially crucial for highly innovative companies. In addition, an HRM regime using practices of all HRM areas has the highest positive association, but a linear ranking of HRM regimes cannot be found. Hence, the more the merrier does not necessarily apply. Rather, the correct combination of HRM practices seems to be crucial.

4.1 Introduction

Innovation as a key element for development and economic growth is undisputed. In addition to extensive market conditions, the human resources have always been regarded as an important parameter. Already Marx (1962) emphasized the value of labor. Following Galbraith (1984) or Vrakking (1990), the human resources are involved in the entire innovation process. The strong involvement is the reason why HRM practices as an aspect of human resources are increasingly recognized as an important element for innovation (Jiménez-Jiménez and Sanz-Valle, 2005; Tidd et al., 1997; Looise and van Riemsdijk, 2004). Following Ulrich and Lake (1990), HRM practices can help a company, to gain a competitive advantage. In addition to the selection of suitable employees, aspects of motivation, training and remuneration are crucial to exploit a company's capability (Hiltrop, 1996: 629).

Laursen and Foss (2003) and Leede and Looise (2005) argue that the interaction of HRM practices and innovation has theoretically been barely mentioned in both, the HRM and the innovation literature.[1] However, the interest of possible interactions between HRM and innovation has been increasing in recent years (Boxall and Purcell, 2003; Leede and Looise, 2005). Based on Jiménez-Jiménez and Sanz-Valle (2005) or Michie and Sheehan (1999), most of the previous studies use data from the United States (US). They focus on outcome variables and mostly show positive, but not consistently unambiguous results.

My empirical work is based on the theoretical model of Leede and Looise (2005), which is arguably the first model to bring together the interactions between HRM and innovation. The used Australian dataset combines information on innovation as well as on human resources for all sectors. In addition to a variety of HRM practices, several variables to describe the innovation activities are included. Thus, a comprehensive measure of innovation according to the complexity of the innovation process can be applied.[2] To define the use of HRM, two additional approaches are used in addition to the individual HRM practices. In order to account for poten-

1 Most of all HRM studies focus on performance measurements. Guest (1997) for example does not list innovation as a relevant performance indicator.
2 Similar to the approach of Webster (2004: 737). See also Hollenstein (1996).

tial complementarities between the various practices, not only a factor analysis but also a subsequent cluster analysis is used to identify groups and whole regimes of HRM practices.

The rest of the paper is structured as follows. At first, a brief definition of HRM and its elements is given in Chapter 4.2. A literature review is given in Chapter 4.3. Chapter 4.4 describes a theoretical model that summarizes possible interactions between HRM and innovation. Based on the model, some hypotheses can be derived. To empirically test the hypotheses, the data and the empirical model are presented in Chapter 4.5 and 4.6, respectively. Chapter 4.7 summarizes the results. Finally, Chapter 4.8 gives some conclusions.

4.2 Human resource management

Following Beer (1984), HRM includes all activities and decisions of a company relating to its human resources. The overall objective of HRM, as stated by Armstrong (2009), is to ensure that an organization is able to achieve its goals by making the best possible use of the available human resources.

HRM comprises a plurality of possible practices. They can be divided into four main groups of practices, listed in Table 4.1.[3] The first category contains practices to change the design of the individual tasks as well as the responsibilities of the employees within an organization. It includes HRM practices such as job enrichment, group work or job rotation. The second category includes all practices designed for the selection, implementation, development and termination of employees. Practices to measure the performance and the appropriate remuneration of the employees are part of the third category. Potential HRM practices include job evaluation, incentive pay, bonuses or profit sharing. The last category summarizes activities related to the communication between a company and its employees. It includes not only adequate information and transparency, but also practices to participate in decision-making.

[3] General information for a further subdivision of these areas into separate groups of practices can be found in e.g. Bratton and Gold (2007) or Armstrong (2009). The list is not to be exhaustive and does not contain information on the effectiveness or weighting of individual practices. Rather, the list should give an overview of HRM areas. See e.g. Hiltrop (1996: 629) for more information.

Table 4.1: Categories of HRM practices, based on Beer (1984).

Category		HRM practices
1	Task assignment	Task definition Job rotation Group work
2	Job flow	Selection Recruitment Implementation Training Development Termination
3	Performance assessment	Job evaluation Incentive pay Bonuses Profit sharing
4	Communication	Communication Information Participation

The interest in HRM practices and their potential impact on the outcomes of a company has risen significantly in recent decades (Laursen and Foss, 2003; Leede and Looise, 2005). Following Boxall and Purcell (2003), three primary schools of HRM and corporate strategy can be distinguished.[4] The best known school is the so-called contingency approach. Developed by Fombrun et al. (1984) in the early 1980s, the approach emphasizes how HRM practices should be consistent with the company's strategy. The individual practices and their combination have to fit the needs of the company externally and internally (Hiltrop, 1996: 629). Therefore, the approach is also referred to as the best-fit approach. Following Fombrun et al. (1984), selection, performance appraisal, rewards and employee development are particularly important as HRM elements in order to achieve this fit. The study of Schuler and Jackson (1987) can also be assigned to the best-fit approach. Using the competitive strategies developed by Porter (1998), Schuler and Jackson define a specific set of HRM practices. Miles and Snow (1984) direct their HRM systems according to the four different firm strategies `Defender', `Prospector', `Analyser' and `Reactor'.[5]

The second school is the best practice approach. It assumes that there exists an ideal set of HRM practices for the enhancement of a company's output, regardless of oth-

4 Additional theoretical approaches can be found, see Hiltrop (1996: 631-632).
5 For more information about the model advancements see Hiltrop (1996: 629-630) or Leede and Looise (2005: 110).

er company characteristics or market factors. This set is based on empirical evidence about performance improvements after the implementation of HRM practices. Following the best practice approach, the implementation of the proved ideal set will always increase the result of all companies. The best known example is the list of 16 practices given by Pfeffer (1994).

The resource approach is the third school. It is based on the assumption that the human capital resources represent a source of competitive advantage. Following Barney (1991), HRM practices should accordingly be designed to educate and motivate the employees. At the same time, they can help to build a suitable resource pool, which is hard to imitate by competitors.[6]

4.3 Literature review

Most of the previous empirical studies on the HRM practices listed in Table 4.1 either focus on the influence of individual practices or consider the impact of HRM on outcome variables such as productivity or profit using data from the US (Huselid, 1995: 643; Delaney and Huselid, 1996; Michie and Sheehan, 1999) A survey of previous studies can be found in Dyer and Reeves (1994) or Guest (1997, 2001).

The results for some practices are univocal. It is generally agreed that the careful selection of new hires is an important factor for the successful strategy of a company (Miles and Snow, 1984: 42) as well as for innovation (Jiménez-Jiménez and Sanz-Valle, 2005: 366). Among others, Jackson et al. (1989) argue that the selection system should identify candidates who see changes and innovations as a challenge, which is confirmed by the empirical results of Raghuram and Arvey (1994). A similar result can be found for remuneration practices. Miles and Snow (1984), Schuler and Jackson (1987) and Gómez-Mejía (1992) show a positive influence of compensation practices such as incentive pays. Additionally, Michie and Sheehan (1999) and Laursen and Foss (2003) demonstrate a positive correlation between and incentive wages and innovation.

[6] More information about the resource approach can be found in Hiltrop (1996: 633).

However, not all individual practices show unambiguous results. Following Jackson et al. (1989) or Keep (1999), training is considered to be an important prerequisite in order to adapt the skills of the employees. Jackson et al. (1989) and Shipton et al. (2006) confirm a positive correlation between innovation and training practices. In contrast, in some cases training can also cause undesirable results, as demonstrated by Raghuram and Arvey (1994). Following Levinthal and March (1993), training does not support creativity such as discovery learning. Some researchers therefore advise to use the required skills from the external labor market (Jiménez-Jiménez and Sanz-Valle, 2005: 367). Ambiguous results can also be found for appraisal practices. Although McGregor (1960) stated that appraisals are judgmental and thus able to de-motivate, a fundamentally positive relationship is assumed. Following Mabey and Salaman (1995) and Gupta (1993), performance appraisals are theoretically considered as an important HRM practice in terms of innovation. This relationship is demonstrated by empirical studies such as given by Jackson et al. (1989) or Shipton et al. (2006). Nevertheless, there are disagreements about the exact impact.

Although the positive influence of individual practices such as selection methods or incentive pay can be more or less confirmed, the results of previous empirical studies mostly vary and the observed impacts are usually not very high (Hiltrop, 1996: 629). However, the discrepancies can also be attributed to the different datasets and empirical models. In addition, some studies consider only individual practices, while in other studies, bundles of individual policies or whole HRM regimes are examined. In most cases, not just one individual practice, but groups of HRM practices are carried out. Following Ichniowski et al. (1997: 295) or Holmstrom and Milgrom (1994: 990), these groups can also be connected. For example, group work can be associated with practices that motivate teamwork such as incentive pay or flexible work contracts. Fombrun (1984), Macduffie (1995) and Ichniowski et al. (1997) show that internally consistent HRM bundles have a much higher impact than individual practices.

Studies on HRM and innovation that take into account for complementarities are very rare. The analysis of Ichniowski et al. (1997) is one of the first comprehensive studies dealing empirically with the context of HRM and innovation. They refer to the high importance of complementarities between the different practices and form seven groups of HRM practices based on case studies of US firms in the steel production market. It turns out that companies with innovative HRM regimes have a much higher productivity. However, the results are not comparable or transferable to other sectors. A more cross-industry study is conducted by Michie and Sheehan (1999). Their classification of HRM regimes is more generally based on the number of practices applied within a company. Companies in the lowest regime have no HRM practice, while firms in the innovative regime consider at least one practice from each group of HRM practices. The results show a positive correlation between the innovative regime and research expenditures. The study of Ling and Nasurdin (2010) analyzes the impact of five HRM practices on different types of innovations. The results show a consistently positive effect of training measures. However, payment practices act negatively on new products, while recruitment measures reduce process innovations. Finally, Jiménez-Jiménez and Sanz-Valle (2005) consider the relationship between HRM and innovation using data from Spanish companies. Their study confirms a positive relationship between HRM bundles and innovation. In addition, they also involve the question of the direction of causality. Thereby, HRM practices can affect the innovation levels of a company, but the other way around innovation can also define the company's HRM system.

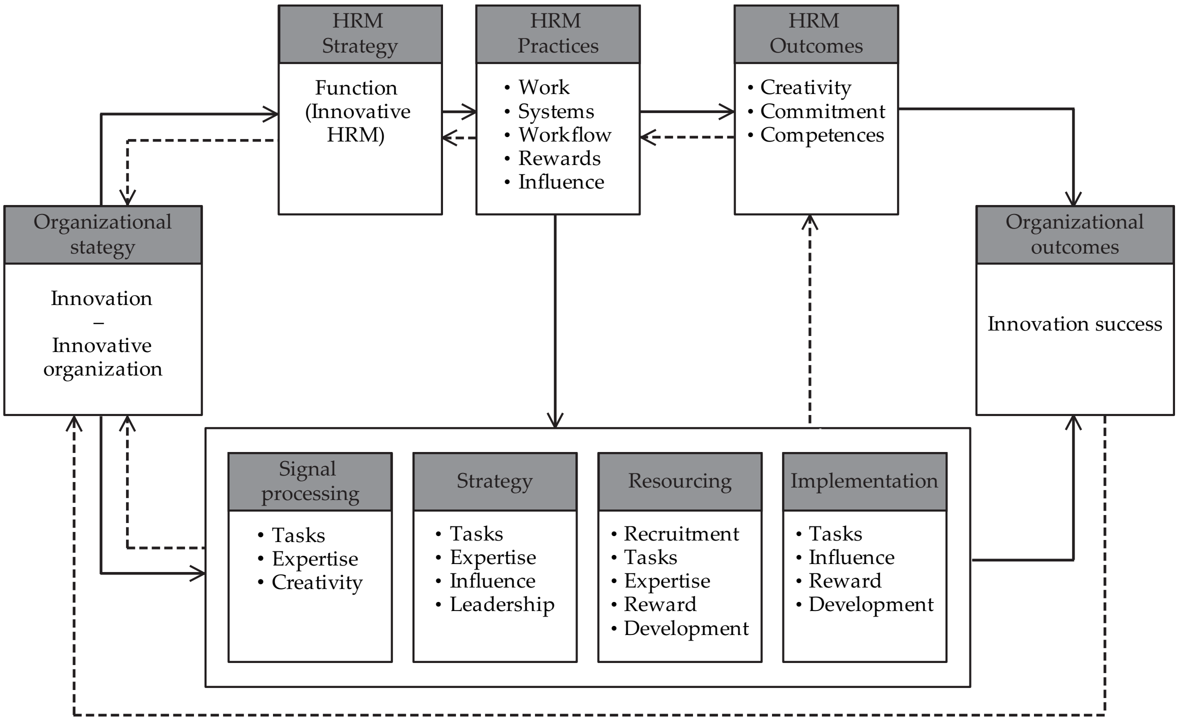
Summarizing previous theoretical and empirical results, it can be stated that there is no single best HRM practice, neither for performance indicators nor for innovation (Hiltrop, 1996). Rather, the correct combination of individual practices seems to be crucial. In addition, the effect depends on the phase in the innovation process or the type of the implemented innovation.

4.4 Theoretical model

This paper is based on the theoretical model of Leede and Looise (2005). Although there is separate research on innovation and HRM, a model to integrate both topics has previously not been developed. Existing HRM theories, on the one hand, are much more general and relate to organizational results or strategies such as the box model of Guest (1997). Previous innovation studies, on the other hand, consider HRM as an additional instrument rather than as an integrative element (Leede and Looise, 2005: 108). Bringing together innovation and HRM, Leede and Looise (2005) look at the innovative company as a whole as well as at individual innovation activities within a company. They build their models in line with the previous literature and based on a case study. Starting from the case study, a link between individual HRM practices and certain types of innovation prove to be difficult. Instead, it appears that the individual management practices are associated with certain phases in the innovation process. Following Leede and Looise (2005), this applies to all types of innovations such as new products, processes and organizational innovations, respectively.

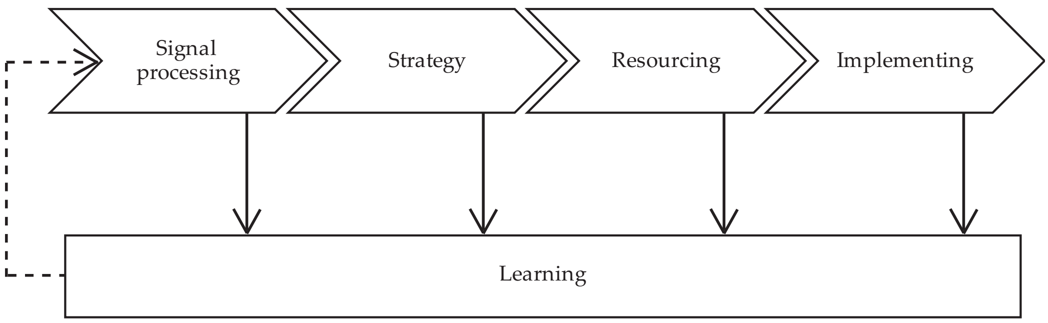
The model is shown in Figure 4.1. It begins on the left hand side with the company's organizational strategy, which refers to innovation as a whole and not only to individual aspects such as cost reductions. The end on the right hand side is the result of the organizational strategy. The outcome includes the success of the innovation efforts, measured by indicators such as the number of new processes or the turnover with new products. However, the beginning and the end point are not strictly separated from each other. Both are rather connected, because the result in turn influences the innovation strategy. Therefore, an absolute starting point cannot be determined. Both points are rather understood as moments to measure objectives and results. Between the two moments, two connecting levels are distinguished. The first level, in Figure 4.1 shown at the top, includes HRM aspects that affect the whole organization of a company. The practices listed up there should help the company to be a creative and innovative organization. A HRM strategy is built to achieve this. The HRM strategy can either be built on HRM standard systems or be constructed by a function of specifically targeted individual practices, such as working conditions, employee selection or reward systems. In total, the function has to be aimed at an innovative outcome such as supporting creativity or commitment. Thereby, the company has to adjust the HRM standard system or the individual HRM components to the firm's specific innovation strategy.

Figure 4.1: Model by Leede and Looise (2005).



The second level between the start and end moment refers to the individual phases of an innovation process. According to the model of Tidd et al. (1997), the individual stages of the innovation process include signal processing, strategy, resourcing, implementing and learning. The phases are illustrated in Figure 4.2.

Figure 4.2: Phases of the innovation process based on Tidd et al. (1997).



During the first stage, signals for changes are collected on internal and external levels. The processing involves the scan of the environment as well as the detection of relevant options and associated risks. Subsequently, a company chooses the best realizable signal during the strategy phase. The decision is based on the results of the searching process, the company's strategy as well as its capabilities. During resourcing, solutions for the realization are sought, for example by internal or external R&D, technology transfer or benchmarking. The next stage includes implementing. The idea is translated into a new product, service or process. The internal or external market introduction of the innovation as well as the testing and further developments are also part of this phase. Throughout all the steps of the innovation process, the company accumulates knowledge and experience which in turn can be used for a new signal processing.

Each phase of the innovation process requires specific HRM methods. Creativity and the development of necessary expertise and experience are essential for the signal processing as well as the strategy phase. Hence, HRM practices such as appropriate selection criteria of the involved employees, training or group work as a possibility for the creative exchange of ideas would be conceivable. The second phase additionally claims for different channels of influence and management leadership. Appropriate selection processes as well as communication and participation practices could be a part of this stage. The coordinated recruitment and targeted future development are HRM components of the third phase. For implementation, a coordinated rewarding system based on incentive pay as well as participation and training seems to be crucial. Some practices are relevant in various phases of the innovation process, although the respective content may differ. That applies to the assignment of tasks, the training or the payment of the employees.

Based on the underlying theoretical model and the results of previous studies, I derive three hypotheses to be tested empirically. According to the first level in the model, HRM practices are particularly important, the more the strategy focuses on innovation. According to the second level in the model, certain practices are used, depending on the phase of the innovation process. Practices that are used in several phases are particularly important for innovating companies.

Hypothesis I HRM practices affect the innovation performance of a company, particularly in the case of highly innovative companies. In addition, practices that are used repeatedly in the innovation process are particularly important. This includes practices such as task assignment, training or incentive pay.

Considering the two distinct levels, however, several practices can influence the innovation strategy or the individual phases of the innovation process. Based on previous empirical studies, usually not only individual practices are carried out. Some practices act similarly and can be assigned to the same category of HRM practices. As stated by Holmstrom and Milgrom (1994) or Ichniowski et al. (1997), the effect of grouped complementary practices is significantly higher.[7]

Hypothesis II Grouping HRM factors enhance the correlation between human resource activities and innovation. Again, not all factors are equally important for every innovation phase.

Following Ichniowski et al. (1997) and Michie and Sheehan (1999), not only similar practices from the same category can be summarized, but especially the right combination of different practices is crucial.

Hypothesis III The direction and strength of the correlation depends on the combination of different practices, represented in so-called HRM regimes. That does not necessarily mean that more HRM practices automatically lead to increased innovation activities.

The description of the data and the model for empirical verification can be found in the following chapters.

4.5 Data

The data stem from the annually collected Melbourne Institute Business Survey from 2001 to 2010. The contacted companies are the top 1000 Australian companies of the IBISWorld dataset measured by total revenue. The dataset contains extensive details about industrial relations, human resources and management issues. Variables such as firm size or industry affiliation are included by matching the survey with the IBISWorld data.

7 See also Kandel and Lazear (1992), Michie and Sheehan (1999).

A plurality of different HRM variables is available in the dataset. Table 4.2 lists all practices including their mean and standard deviation. With means of 4 to 5, the accordance to all individual practices is very high.

Table 4.2: HRM practices in the survey.

HRM practices		N	Mean	SD
HRM01	Providing formal training programs to teach new employees	2032	4.941	1.421
HRM02	Providing training to keep employees' skills up to date	2033	5.186	1.145
HRM03	Offering cross-training to increase the number of skills	2030	4.440	1.230
HRM04	Owning a clear and well communicated strategic mission	2032	4.899	1.373
HRM05	Using procedures to communicate important information	2033	5.317	1.168
HRM06	Utilizing teams which have responsibility for decisions	2031	4.643	1.361
HRM07	Involving employees in decisions that directly affect their work	2031	4.860	1.146
HRM08	Acting on suggestions and feedback provided by employees	2029	4.982	1.084
HRM09	Conducting formal appraisals of employee performance	2028	5.245	1.491
HRM10	Providing a formal grievance procedures system for employees	2031	5.596	1.414
HRM11	Offering feedback to address poorly performing employees	2033	4.854	1.369
HRM12	Rewarding employees based on employee performance	2033	4.651	1.501
HRM13	Rewarding employees based on team performance	2030	4.006	1.548
HRM14	Rewarding employees based on organization performance	2032	4.367	1.612
HRM15	Owning a performance appraisal system for effective rewarding	2015	4.518	1.676

Notes: Mean and standard deviation for all HRM items.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

In order to group the HRM items of the same category, a factor analysis is used. The resulting four factors are listed in Table 4.3 and can be characterized unambiguously. *Remuneration* contains practices that are all related to the payment of employees. This applies to different reward systems as well as to an appraisal system to guarantee an effective rewarding. The second factor *Communication* refers to aspects of communication and employee involvement. *Appreciation* contains HRM practices such as performance grievances and appraisals. Finally, *Education* includes aspects of training to maintain and to expand skills.

Table 4.3: Factors of the HRM items.

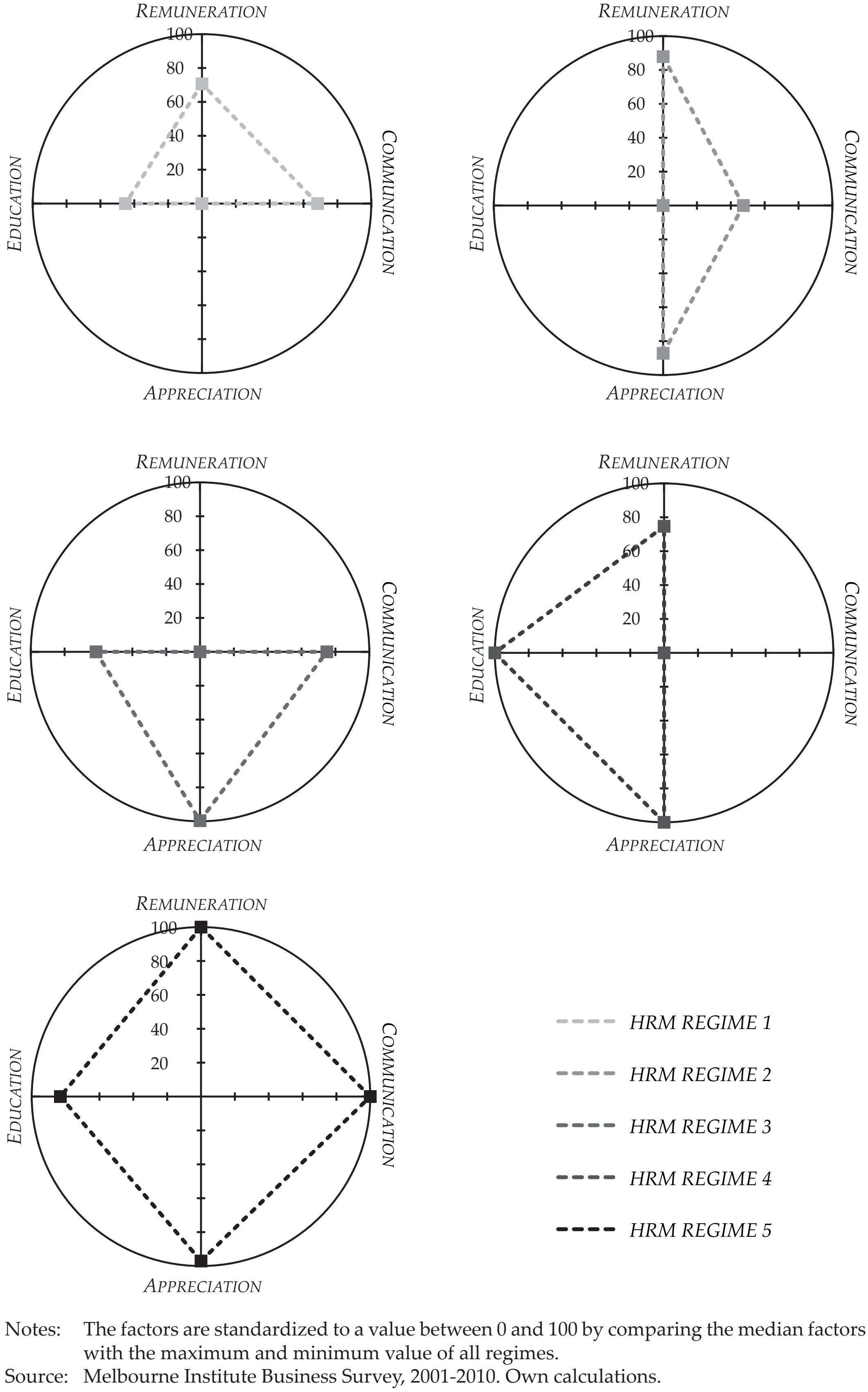
HRM	Variable	Factor	Uniqueness
Remuneration, α= 0.8129			
HRM14	Rewarding employees based on organization performance	0.825	0.305
HRM13	Rewarding employees based on team performance	0.819	0.281
HRM12	Rewarding employees based on employee performance	0.801	0.283
HRM15	Owning a performance appraisal system for effective rewarding	0.719	0.280
Communication, α= 0.8273			
HRM07	Involving employees in decisions that directly affect their work	0.818	0.257
HRM08	Acting on suggestions and feedback provided by employees	0.747	0.337
HRM06	Utilizing teams which have responsibility for decisions	0.696	0.406
HRM04	Owning a clear and well communicated strategic mission	0.550	0.423
HRM05	Using procedures to communicate important information	0.543	0.398
Appreciation, α= 0.7618			
HRM10	Providing a formal grievance procedure system for employees	0.781	0.343
HRM09	Conducting formal appraisals of employee performance	0.714	0.328
HRM11	Offering feedback to address poorly performing employees	0.679	0.383
Education, α= 0.7178			
HRM01	Providing formal training programs to teach new employees	0.766	0.304
HRM03	Offering cross-training to increase the number of skills	0.731	0.368
HRM02	Providing training to keep employees' skills up to date	0.728	0.300

Notes: Factor analysis carried out by a principal component analysis with varimax rotation and the regression method to predict the factors. α is the Cronbach's Alpha for the individual factors.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Based on previous studies such as Ichniowski et al. (1995) or Laursen and Foss (2003), the perfect combination of complementary practices is crucial. For this reason, I additionally consider so-called HRM regimes using a cluster analysis of the HRM factors.[8] Figure 4.3 illustrates the resulting five HRM regimes using the HRM factors. *HRM Regime 1* is the cluster with the lowest use of HRM practices. *HRM Regime 5*, in contrast, represents the strongest HRM regime. All included HRM factors seem to be important for the companies in this cluster. The other three regimes lie between the two extremes. *HRM Regime 2* refers to the utilization of the two factors *Remuneration* and *Appreciation*.

[8] The results of the HRM cluster analysis including mean values of the factors and the individual HRM items can be found in Table 4.8 in the appendix. To determine the number of clusters, two criteria are chosen, listed in Table 4.9 in the appendix. Following the pseudo-F-statistic of Calinski and Harabasz (1974), the optimal number of clusters is associated with the highest value of the pseudo-F statistic. Duda and Hart (1973) stated, a clear cluster classification is associated with a high value of the Duda/Hart index and a small value of the pseudo T-squared statistic. According to both criteria, the data is grouped into five clusters. The occurrence of the regimes over the years 2001-2010 can be found in Figure 4.5 in the appendix.

Figure 4.3: Description of the HRM regimes using the HRM factors *Remuneration*, *Appreciation*, *Communication* and *Education*.



Notes: The factors are standardized to a value between 0 and 100 by comparing the median factors with the maximum and minimum value of all regimes.

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Companies from *HRM Regime 3* show the highest value for *Appreciation* and a high, though not the highest, value for *Communication*. The results of *HRM Regime 4* show very high values for *Education* and *Appreciation* and a high value for *Remuneration*. Due to the generally higher median values, it is classified as the second most powerful HRM regime.

The innovation variable is composed by several items on the innovation behavior, which describe the innovation activities of a company. The choice of this procedure has several reasons. First, the business survey does not provide a definite single innovation indicator. Hence, a company cannot be clearly identified as innovator or non-innovator.[9] Second, the procedure is also much more in accordance with the complexity of the innovation process. The individual variables to describe the innovation activities give information about the resources invested into new products or technologies, the amount of new or improved products and services, the innovation management as well as the competitive strategy of a company. Compared to its competitors, a company can be a technological leader, have a competitive posture or a pioneer position, focus on cost-saving process innovations or be a customer adapter. With the help of a cluster analysis, companies can be assigned to four groups with different innovation status.[10]

Figure 4.4 brings together the resulting innovation clusters and the variables to describe the innovation behavior. The first cluster shows the lowest value of all innovation variables and is therefore called *Non-Innovator*. *Pioneers*, in contrast, are characterized by consistently high values. Hence, the companies in this cluster are highly innovative, especially in terms of the introduction of new or improved products and services, the amount of resources invested in innovation and pioneering tasks compared to the competitors on the market. *Small innovators* can also be

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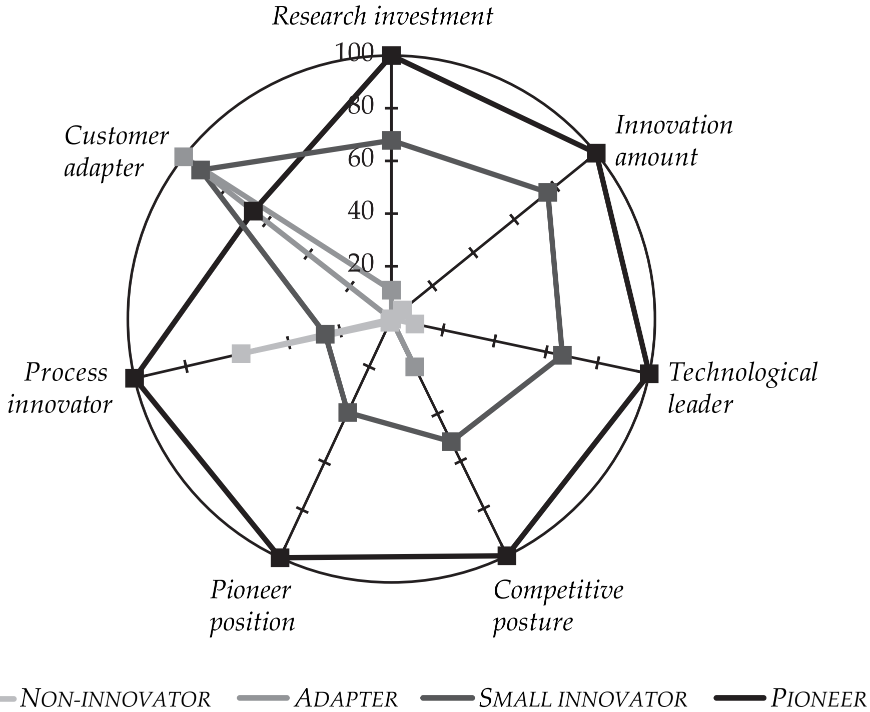
9 Although the matched data set IBISWorld contains the R&D expenditures, the variable shows a high number of missing values. In addition, an under-reporting in accounting data especially for small and medium-sized companies can be observed. See Webster (2004: 738) or Kleinknecht (1996: 1-12) for more information.

10 Previously, a factor analysis is used. The variables included into the factor analysis as well as the resulting factors can be found in Table 4.10 in the appendix. Following the Calinski-Harabasz as well as the Duda/Hart criterion in Table 4.9 in the appendix, a solution with four clusters is found. The occurrence of the innovation cluster over the years 2001-2010 can be found in Figure 4.6 in the appendix.

described as innovative. Compared to the *Pioneers*, however, they have lower expenses for innovation and a lower number of new products or services. Moreover, they are neither flexible adapters of customer requirements nor process innovators, while *Pioneers* are characterized by innovation in all areas.

Figure 4.4: Description if the cluster using the innovation factors.



Notes: The factors are standardized to a value between 0 and 100 by comparing the median factors with the maximum and minimum value of all regimes.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Finally, *Adapters* show negative values for almost all factors. However, these companies focus on customer adjustments as well as effectiveness increases and cost reductions in the form of process innovations.

Table 4.4 contains some descriptive statistics for the further description of the dataset and the innovation clusters. With a value of nearly 72 percent, most of all companies are in Australian property. The share of companies with foreign ownership is higher for *Small Innovators* and *Pioneers*. The manufacturing and wholesale industries as well as the finance, insurance and business services are the most strongly represented sectors. Half of all companies can be assigned to a service sector. 20 percent belong to an administrative or public sector. Nearly 50 percent of the observations have less than 500 employees. Only six percent have 5,000 employees or more.

Table 4.4: Summary of descriptive statistics, percentage.

Variables	All	*Non-innovator*	*Adapter*	*Small Innovator*	*Pioneer*
Innovation status					
Non-innovator	19.19				
Adapter	22.59				
Small Innovator	28.43				
Pioneer	29.78				
Total	100.00				
Ownership					
Local	71.84	76.34	75.08	69.42	64.3
Foreign	28.16	23.66	24.92	30.58	35.7
Total	100.00	100.00	100.00	100.00	100.00
Sectors					
Agriculture	1.15	1.15	2.74	0.6	0.7
Utilities and Mining	8.92	8.92	21.58	7.14	5.36
Manufacturing	18.51	18.51	14.73	16.07	19.81
Construction	4.37	4.37	1.71	8.33	4.2
Trade	20.15	20.15	17.81	21.13	23.08
Transport and Storage	12.99	12.99	9.93	16.37	15.38
Finance and Insurance	12.56	12.56	7.19	12.8	12.12
Business Services	13.77	13.77	20.21	10.71	9.09
Administration	4.55	4.55	3.08	2.08	6.99
Education	3.03	3.03	1.03	4.76	3.26
Total	100.00	100.00	100.00	100.00	100.00
Employment size					
Less than 200	25	23.05	32.2	24.66	22.07
200 to under 500	22.55	21.75	24.58	24.43	22.07
500 to under 1000	23.14	25.32	18.93	21.95	20.72
1000 to under 5000	23.19	25.32	19.21	23.76	25.68
5000 or more	6.12	4.55	5.08	5.2	9.46
Total	100.00	100.00	100.00	100.00	100.00
Human resource managament (HRM)					
Remuneration	0.188	-0.263	0.090	0.315	0.431
Communication	0.046	-0.341	-0.136	0.130	0.253
Appreciation	0.125	-0.012	0.056	0.109	0.219
Education	0.074	-0.147	0.065	0.007	0.241
HRM Regime 1	24.11	30.00	29.30	23.02	18.45
HRM Regime 2	32.45	32.29	30.99	35.98	32.47
HRM Regime 3	12.26	16.57	10.17	10.83	8.49
HRM Regime 4	10.85	10.29	13.08	6.77	12.92
HRM Regime 5	20.34	10.86	16.46	23.4	27.68
Total	100.00	100.00	100.00	100.00	100.00

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

However, the proportion of companies with more than 1,000 employees is significantly higher for *Pioneers*, especially compared to *Adapters*. Considering the HRM factors, *Non-Innovators* have only negative median values. *Adapters* have positive, but only very small values for *Remuneration*, *Appreciation* and *Education*. *Pioneers* and *Small innovators* have only positive values, but the median factors are higher for *Pioneers*.

Although more than 20 percent of all companies across all years belong to the strongest *HRM Regime 5*, the first two weaker regimes contain more than half of all observations. The distribution of the HRM regimes shows a significantly higher proportion of *HRM Regime 5* for *Small Innovators* and *Pioneers*. In addition, the shares of *HRM Regime 1* and *HRM Regime 2* are significantly higher for *Non-Innovators* and *Adapters*, while *Small Innovators* and *Pioneers* show higher shares of the fourth and fifth regime. However, a clear ranking between the regimes is not recognizable.

4.6 Empirical model

To test the hypotheses, I calculate an Ordered Probit regression model using the innovation cluster *Inno* as dependent variable. The model can be written as

$$Prob(\textit{Inno}=1,2,3,4 \mid X) = \Phi\,(X'\beta) + \varepsilon, \quad \text{where } \textit{Inno} = \begin{cases} 1 & \textit{Non-innovator} \\ 2 & \textit{Adapter} \\ 3 & \textit{Small Innovator} \\ 4 & \textit{Pionier} \end{cases} \qquad (1)$$

Thereby, X is a vector of independent variables and Φ represents the Cumulative Distribution Function of the standard normal distribution. The model can be interpreted as the probability of a company to belong to one of the innovation clusters given the variables summarized in X. First of all, the different HRM variables as individual practices, factors and clusters are used as explanatory variables in the vector X. In addition to the HRM practices, I use several control variables. In order to control for the competitive position of the company, the variable *Firm* is used. It contains summarized variables describing the current position of the company in relation to the competitors, such as the rate of return on capital, customer retention, market share growth and employee productivity.[11] To specify the market, I use the two variables *TechMar* and *CompMar*. They contain several statements about the market situation of a company. Thereby, *TechMar* describes a market, where technologies as well as marketing practices are subject to much change and products or services quickly become obsolete. The actions of competitors and consumers are hard to predict. Hence, the higher the value of the variable *TechMar*, the higher the uncertainty of the market. *CompMar* represents a strongly fragmented market with little market power and high entry barriers. In this market, finding suitable labor is difficult.[12] In addition, dummy variables for different *Size* groups are included. *Foreign* indicates foreign owned companies. Finally, dummies for the sectors *Sec* and the years *Year* are included.

First of all, the individual HRM practices *HRM01 – HRM15* are included. Equation (1) can be written as

$$Prob(Inno|X) = \Phi(\beta_0 + \beta_1 \cdot HRM01\text{-}HRM15 + \beta_2 \cdot Firm + \beta_3 \cdot TechMar + \beta_4 \cdot CompMar + \beta_5 \cdot Foreign + \beta_6 \cdot Sec + \beta_7 \cdot Year), \quad (2)$$

with *Inno=1,2,3,4*. In equation (3), the grouping HRM factors *Remuneration*, *Communication*, *Appreciation* and *Education* are used as indicators of the HRM activities. They account for possible complementarities between the single practices.

$$Prob(Inno|X) = \Phi(\beta_0 + \beta_1 \cdot HRM\ factor1 - HRM\ factor4 + \beta_2 \cdot Firm + \beta_3 \cdot TechMar + \beta_4 \cdot CompMar + \beta_5 \cdot Foreign + \beta_6 \cdot Sec + \beta_7 \cdot Year) \quad (3)$$

Finally, equation (4) includes the different *HRM Regimes*.

$$Prob(Inno|X) = \Phi(\beta_0 + \beta_1 \cdot HRM\ Regime1 - HRM\ Regime4 + \beta_2 \cdot Firm + \beta_3 \cdot TechMar + \beta_4 \cdot CompMar + \beta_5 \cdot Foreign + \beta_6 \cdot Sec + \beta_7 \cdot Year) \quad (4)$$

The different regression equations with the included variables and their encodings are summarized in Table 4.13 in the appendix.

[11] Due to the aforementioned difficulties with the account data, the annual turnover cannot be used. The variables result from a factor analysis listed in Table 4.12 in the appendix.

[12] Both variables also result from a previous factors analysis, listed in Table 4.12 in the appendix.

4.7 Results

The results of the different regression equations are summarized in Table 4.5 to Table 4.7. The results of equation (2) in Table 4.5 are diverging. Most of all HRM practices are positively correlated with the probability to innovate.

Table 4.5: Marginal effects of the Ordered Probit regression, equation (2).

Inno	(2)											
	Non-Innovator			Adapter			Small Innovator			Pioneer		
HRM01	-0.004	(0.004)		-0.002	(0.002)		0.001	(0.001)		0.006	(0.005)	
HRM02	-0.005	(0.005)		-0.002	(0.003)		0.001	(0.001)		0.007	(0.007)	
HRM03	-0.003	(0.004)		-0.001	(0.002)		0.000	(0.001)		0.004	(0.006)	
HRM04	-0.005	(0.004)		-0.003	(0.002)		0.001	(0.001)		0.008	(0.006)	
HRM05	-0.013	(0.005)	**	-0.007	(0.003)	**	0.002	(0.001)	**	0.018	(0.007)	**
HRM06	0.005	(0.004)		0.002	(0.002)		-0.001	(0.001)		-0.006	(0.006)	
HRM07	0.007	(0.005)		0.004	(0.003)		-0.001	(0.001)		-0.010	(0.007)	
HRM08	-0.033	(0.006)	***	-0.017	(0.003)	***	0.005	(0.001)	***	0.046	(0.008)	***
HRM09	0.000	(0.004)		0.000	(0.002)		0.000	(0.001)		0.000	(0.006)	
HRM10	-0.009	(0.004)	**	-0.005	(0.002)	**	0.001	(0.001)	**	0.012	(0.005)	**
HRM11	0.004	(0.004)		0.002	(0.002)		-0.001	(0.001)		-0.006	(0.006)	
HRM12	-0.015	(0.004)	***	-0.007	(0.002)	***	0.002	(0.001)	***	0.020	(0.006)	***
HRM13	-0.010	(0.004)	**	-0.005	(0.002)	**	0.001	(0.001)	**	0.014	(0.005)	**
HRM14	-0.015	(0.004)	***	-0.008	(0.002)	***	0.002	(0.001)	***	0.021	(0.005)	***
HRM15	0.012	(0.004)	***	0.006	(0.002)	***	-0.002	(0.001)	***	-0.017	(0.005)	***
Firm	-0.024	(0.005)	***	-0.012	(0.002)	***	0.003	(0.001)	***	0.033	(0.006)	***
TechMar	-0.086	(0.005)	***	-0.043	(0.003)	***	0.012	(0.002)	***	0.117	(0.006)	***
CompMar	0.024	(0.005)	***	0.012	(0.002)	***	-0.003	(0.001)	***	-0.033	(0.006)	***
Foreign	0.011	(0.011)		0.005	(0.005)		-0.002	(0.002)		-0.014	(0.014)	
Size1	0.048	(0.024)	**	0.020	(0.008)	**	-0.010	(0.007)		-0.058	(0.025)	**
Size 2	0.063	(0.024)	***	0.025	(0.007)	***	-0.015	(0.007)	**	-0.073	(0.023)	***
Size 3	0.041	(0.023)	*	0.018	(0.008)	**	-0.008	(0.006)		-0.050	(0.025)	**
Size 4	0.031	(0.021)		0.014	(0.008)		-0.006	(0.005)		-0.039	(0.025)	
Size 5	--	--		--	--		--	--		--	--	
Years		Yes			Yes			Yes			Yes	
Sec		Yes			Yes			Yes			Yes	
N		225			279			368			367	
Chi²						467.63***						
Pseudo-R2						0.1381						
LL						-1459.2421						

Notes: Calculated using the Stata ado-file of Bartus (2005). Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Variables measuring feedback, rewarding as well as communication show the highest positive and also significant values. The first hypothesis, assuming a positive correlation especially for HRM practices that are used in several phases of the innovation process, can be confirmed. In addition, the coefficients are larger for companies that are classified as highly innovative *Pioneers*. Negative coefficients can be found in some practices relating to training, group work or transparent assessment systems. The discrepancies are partially consistent with the results of previous studies. In addition, they can also be attributed to potential complementarities between the individual practices.

The marginal effects as well as the significance levels rise significantly, when the grouping HRM factors are used in equation (3), shown in in Table 4.6. All included factors are positively and significantly associated with *Small innovators* and *Pioneers*.

Table 4.6: Marginal effects of the Ordered Probit regression, equation (3).

Inno	(3)											
	Non-innovator			*Adapter*			*Small Innovator*			*Pioneer*		
Remuneration	-0.043	(0.005)	***	-0.022	(0.003)	***	0.006	(0.001)	***	0.059	(0.007)	***
Communication	-0.038	(0.005)	***	-0.019	(0.002)	***	0.005	(0.001)	***	0.052	(0.006)	***
Appreciation	-0.019	(0.005)	***	-0.010	(0.002)	***	0.003	(0.001)	***	0.026	(0.006)	***
Education	-0.024	(0.004)	***	-0.012	(0.002)	***	0.003	(0.001)	***	0.032	(0.006)	***
Firm	-0.028	(0.005)	***	-0.014	(0.002)	***	0.004	(0.001)	***	0.038	(0.006)	***
TechMar	-0.085	(0.005)	***	-0.043	(0.003)	***	0.012	(0.002)	***	0.116	(0.006)	***
CompMar	0.026	(0.005)	***	0.013	(0.002)	***	-0.004	(0.001)	***	-0.036	(0.006)	***
Foreign	0.009	(0.011)		0.004	(0.005)		-0.001	(0.002)		-0.012	(0.014)	
Size1	0.047	(0.023)	**	0.019	(0.008)	**	-0.010	(0.007)		-0.056	(0.025)	**
Size 2	0.061	(0.024)	**	0.024	(0.007)	**	-0.014	(0.007)	*	-0.071	(0.023)	***
Size 3	0.045	(0.023)	*	0.019	(0.008)	**	-0.010	(0.006)		-0.054	(0.025)	**
Size 4	0.034	(0.022)		0.015	(0.008)	*	-0.007	(0.005)		-0.042	(0.025)	*
Size 5	--	--		--	--		--	--		--	--	
Years		Yes			Yes			Yes			Yes	
Sec		Yes			Yes			Yes			Yes	
N		225			279			368			367	
Chi^2	441.84***											
Pseudo-R2	0.1305											
LL	-1472.1407											

Notes: Calculated using the Stata ado-file of Bartus (2005). Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

In contrast, the probability to be a *NON-INNOVATOR* or an *ADAPTER* is reduced by the use of all factors. The results confirm the second hypothesis, which assumes a higher correlation for the grouping of HRM factors. Again, HRM practices that are used in various phases of the innovation process show a stronger correlation, particularly with *PIONEERS*. Thereby, aspects of *REMUNERATION* have the highest coefficients, followed by an enhanced corporate *COMMUNICATION*. The factors *APPRECIATION* and *EDUCATION* including assessment as well as training practices are slightly lower.

The marginal effects of the *HRM REGIMES 1* to *4* shown in Table 4.7 are to be interpreted in relation to the *HRM REGIME 5* as the group of companies with the highest usage of HRM practices. Compared to *HRM REGIME 5*, all other regimes reduce the probability to be an innovator.

Table 4.7: Marginal effects of the Ordered Probit regression, equation (4).

INNO	(4)											
	NON-INNOVATOR			*ADAPTER*			*SMALL INNOVATOR*			*PIONEER*		
HRM REGIME 1	0.051	(0.016)	***	0.021	(0.005)	***	-0.012	(0.005)	**	-0.060	(0.016)	***
HRM REGIME 2	0.035	(0.014)	**	0.015	(0.005)	***	-0.007	(0.004)	**	-0.042	(0.015)	***
HRM REGIME 3	0.086	(0.021)	***	0.030	(0.005)	***	-0.023	(0.008)	***	-0.093	(0.019)	***
HRM REGIME 4	0.045	(0.019)	**	0.019	(0.007)	***	-0.010	(0.005)	*	-0.054	(0.020)	***
HRM REGIME 5	--	--		--	--		--	--		--	--	
FIRM	-0.046	(0.005)	***	-0.023	(0.002)	***	0.007	(0.001)	***	0.061	(0.006)	***
TECHMAR	-0.097	(0.005)	***	-0.048	(0.003)	***	0.015	(0.002)	***	0.130	(0.006)	***
COMPMAR	0.033	(0.005)	***	0.016	(0.002)	***	-0.005	(0.001)	***	-0.044	(0.006)	***
FOREIGN	0.002	(0.011)		0.001	(0.005)		0.000	(0.002)		-0.002	(0.014)	
SIZE1	0.049	(0.024)	**	0.020	(0.008)	**	-0.011	(0.007)		-0.058	(0.025)	**
SIZE 2	0.062	(0.024)	**	0.024	(0.007)	***	-0.015	(0.008)	*	-0.071	(0.024)	***
SIZE 3	0.039	(0.023)	*	0.017	(0.008)	**	-0.008	(0.006)		-0.047	(0.026)	*
SIZE 4	0.033	(0.022)		0.014	(0.008)	*	-0.007	(0.006)		-0.040	(0.025)	
SIZE 5	--	--		--	--		--	--		--	--	
YEARS		Yes			Yes			Yes			Yes	
SEC		Yes			Yes			Yes			Yes	
N		225			279			368			367	
Chi^2						378.69						
Pseudo-R2						0.1118						
LL						-1503.7141						

Notes: Calculated using the Stata ado-file of Bartus (2005). Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

The strongest negative association compared to *HRM Regime 5* can be found in *HRM Regime 3* including practices such as communication, training and performance appraisal. Following the marginal effects, the chance of a company of belonging to the group of *Small innovators* is reduced by up to two percent. *Pioneers* are almost ten percent less likely. In addition, companies in *HRM Regime 3* are more than eight percent more likely to be a *Non-Innovator*. In contrast, the second HRM regime shows the second best correlation after *HRM Regime 5*. The companies in this regime, including the most important factors *Remuneration* and *Communication*, are only about four percent less likely of being a pioneering company than in *HRM Regime 5*. Hence, a linear relationship between the HRM regimes and innovation cannot be found, as expected in the third hypothesis. The marginal effects of the control variables are very similar in each regression equation. The variable *Firm* shows a positive correlation. A company with a good position compared to its competitors in terms of return on capital, market volume, customer loyalty and productivity is more likely to be a *Pioneer* by up to six percent. In addition, the characteristics of the market are important. The probability of belonging to the group of *Small Innovators* or *Pioneers* increases, when the market is characterized by *TechMar* with rapid technological changes and a difficult predictability of customers and competitors. In contrast, a competitive market with many operating firms, only slight market power and low entry barriers *CompMar* reduces the innovation activities. Although the results for the company size *Size1-Size4* imply a positive association between large firms and innovation, the marginal effects are not consistently significant for all groups of *Inno*. However, *Adapters* show a remarkably higher level of significance, whereas *Size* is not significantly correlated with *Small innovators*.

According to the theoretical model, an absolute beginning and ending point is not determinable. On the one hand, individual HRM practices, groups of measures or whole HRM regimes can serve to increase the innovative activities of a company. On the other hand, innovation activities also lead to increased knowledge and new experience, which can be used to introduce new or improved innovation strategies. Following the model in Figure 4.1, changed strategies require new and complementary HRM strategies. Hence, previous innovations can influence the HRM practices of a company carried out in the future. To examine this possible reverse causality, equation (3) and (4) are calculated again with lagged values for HRM factors and regimes. The results can be found in Table 4.14 in the appendix. Due to the limited number of companies that are included in the dataset in several years, the number of observations drops significantly. Most of the HRM factors are still negatively associated with *Non-Innovators* and *Adapters* and positively correlated with *Small Innovators* and *Pioneers*. Considering the HRM regimes, it can repeatedly be confirmed that a linear ranking between the regimes does not exist. Therefore, most of all previously described results of equation (3) and (4) can be confirmed, although they do not necessarily reflect a one-way causality.[13]

4.8 Conclusions

The results of the regression equations (2) to (4) show an unambiguous correlation between HRM practices and innovation activities. This applies not only to individual HRM practices, but especially to grouping HRM factors and whole HRM regimes. Regarding individual HRM practices, feedback and acting on suggestions prove to be particularly effective in terms of innovation, due to their use in several phases of the innovation process. The HRM factors, summarizing the individual practices to *Remuneration*, *Communication*, *Appreciation* and *Education*, show a stronger correlation. Thereby, aspects of communication within a company as well as methods of payment again particularly increase the probability to innovate. The marginal effects and the significance levels additionally rise by the use of HRM regimes in equation (4). *HRM Regime 5*, using all the grouping HRM factors most strongly, shows the highest positive association with innovation. The use of practices of *Remuneration*, *Communication*, *Appreciation* and *Education*, therefore, seems to support an innovation strategy. Nevertheless, details about the exact combination and scale of the applied practices cannot be derived. The question of the ideal bundle of HRM practices remains still open and requires further research.

[13] Additonally, a correlation matrix of the independent variables as well as additonal descriptive statistics can be found in Table 4.15 and 4.17.

In addition to the positive association of certain HRM groups, differences depending on the strength of the innovation activities can be found. For a more precise description of the complex innovation processes, the description of the innovation activities is based on several innovation related variables. Considering the resulting four types of innovators, the correlation with *Pioneers* is much stronger than with the less innovative group of *Small innovators*. In addition, the results for all equations are significantly more negative for *Non-Innovators* than for *Adapters*.

Finally, it can be summarized that there is a positive relationship between HRM and innovation activities. Particularly methods of *Communication* and *Remuneration* increase the probability of belonging to one of the innovating groups. Thereby, HRM practices are especially crucial for highly innovative companies that can be assigned to the group of *Pioneers*. In addition, using a combination of all HRM areas as in *HRM Regime 5* has the highest coefficients. However, an ideal ranking of the HRM regimes cannot be found. *HRM Regime 2*, limited to the factors *Remuneration* and *Appreciation*, has the second strongest association with the probability to be a *Pioneer* after *HRM Regime 5*. Hence, the more the merrier does not apply here. Rather, the right combination of HRM practices depending on the innovation strategy and the phase in the innovation process seems to be most important. A perspective for future research is the analysis of this combination as well as potential repercussion effects of innovation activities on the structure of HRM strategies using panel data.

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Appendix

Table 4.8: Results of the HRM cluster analysis.

Variable	*HRM Regime 1*			*HRM Regime 2*			*HRM Regime 3*			*HRM Regime 4*			*HRM Regime 5*		
	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max
Remuneration	-0.17 (0.97)	-3.02	2.05	0.29 (0.72)	-1.94	2.03	-1.56 (0.77)	-3.31	0.19	0.14 (0.65)	-1.46	1.74	0.61 (0.60)	-1.42	2.11
Communication	0.05 (1.15)	-3.88	3.14	-0.18 (0.69)	-2.37	2.82	0.20 (1.07)	-3.02	2.89	-1.07 (0.74)	-2.97	0.68	0.68 (0.67)	-1.85	2.50
Appreciation	-1.27 (0.82)	-4.63	0.70	0.30 (0.69)	-1.74	2.41	0.54 (0.61)	-1.02	1.99	0.47 (0.80)	-1.80	2.28	0.44 (0.52)	-0.95	1.85
Education	-0.09 (1.09)	-3.56	2.94	-0.61 (0.78)	-3.42	1.22	0.26 (0.86)	-2.48	2.47	0.88 (0.74)	-1.41	2.69	0.45 (0.75)	-1.68	1.90
HRM01	4.30 (1.53)	1	7	4.42 (1.20)	1	7	5.30 (1.34)	1	7	5.85 (0.99)	2	7	5.82 (1.04)	2	7
HRM02	4.65 (1.29)	1	7	4.76 (0.96)	2	7	5.52 (0.94)	2	7	5.84 (0.85)	2	7	5.94 (0.78)	3	7
HRM03	4.42 (1.30)	1	7	3.90 (1.05)	1	7	4.28 (1.25)	1	7	4.96 (1.08)	2	7	5.17 (1.00)	2	7
HRM04	4.06 (1.47)	1	7	4.95 (1.16)	1	7	5.10 (1.23)	1	7	4.47 (1.33)	1	7	5.92 (0.83)	3	7
HRM05	4.61 (1.37)	1	7	5.25 (0.95)	2	7	5.60 (0.97)	2	7	5.12 (1.11)	2	7	6.19 (0.67)	4	7
HRM06	4.35 (1.49)	1	7	4.43 (1.12)	1	7	4.61 (1.40)	1	7	3.93 (1.29)	1	7	5.75 (0.86)	2	7
HRM07	4.65 (1.32)	1	7	4.70 (0.86)	2	7	4.93 (1.23)	1	7	4.15 (1.06)	2	7	5.72 (0.79)	3	7
HRM08	4.75 (1.23)	1	7	4.83 (0.86)	1	7	4.89 (1.18)	1	7	4.49 (0.94)	2	6	5.84 (0.74)	4	7
HRM09	3.80 (1.55)	1	7	5.52 (1.09)	2	7	5.32 (1.33)	2	7	5.72 (1.15)	2	7	6.23 (0.84)	2	7
HRM10	4.17 (1.60)	1	7	5.76 (1.03)	1	7	6.38 (0.67)	3	7	6.01 (1.07)	1	7	6.32 (0.81)	1	7
HRM11	3.61 (1.27)	1	6	4.92 (1.12)	2	7	5.05 (1.29)	1	7	5.40 (1.04)	2	7	5.80 (0.86)	3	7
HRM12	4.16 (1.50)	1	7	4.94 (1.14)	2	7	2.94 (1.40)	1	7	4.96 (1.10)	2	7	5.69 (1.04)	1	7
HRM13	3.81 (1.51)	1	7	4.18 (1.34)	1	7	2.24 (1.07)	1	5	3.93 (1.37)	1	7	5.08 (1.19)	1	7
HRM14	4.10 (1.61)	1	7	4.67 (1.32)	1	7	2.43 (1.28)	1	7	4.41 (1.35)	1	7	5.40 (1.16)	1	7
HRM15	3.43 (1.62)	1	7	5.01 (1.19)	1	7	2.95 (1.62)	1	7	4.87 (1.33)	1	7	5.77 (1.00)	2	7
N	480			646			244			216			405		
Use of HRM	Lowest			Low			Medium			High			Highest		

Notes: Standard deviations in brackets.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.9: Calinski/Harabasz and Duda/Hart as indicators to find the right number of HRM and innovation cluster groupings.

	HRM cluster			Innovation cluster		
	Calinski/Harabasz	Duda/Hart		Calinski/Harabasz	Duda/Hart	
	pseudo-F	Je(2)/Je(1)	pseudo T^2	pseudo-F	Je(2)/Je(1)	pseudo T^2
1	--	0.8694	298.68	--	0.7699	552.19
2	298.68	0.8394	288.75	552.19	0.8738	155.32
3	297.42	0.8578	209.76	358.25	0.9057	80.28
4	273.25	0.6983	267.41	**283.19**	**0.8302**	**72.22**
5	**271.22**	**0.8127**	**110.16**	243.48	0.8433	97.37
6	264.46	0.7478	217.22	218.13	0.8499	73.44
7	262.55	0.7129	87.79	201.62	0.866	84.97
8	257.43	0.6857	184.71	190.37	0.7757	45.39
9	250.02	0.7071	106.88	178.85	0.8078	74.00
10	245.48	0.7609	76.03	170.56	0.8939	49.63
11	240.09	0.709	87.84	161.78	0.8739	40.68
12	233.7	0.8274	100.31	154.53	0.8687	51.25

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.10: Innovation variables and resulting factors included in the innovation clusters.

Variable	Factor	Uniqueness
Research investment, α= 0.7011		
During the past 3 years, how many resources have been devoted by to…		
new types of machines, computers, or buildings	0.6111	0.6265
organizational change	0.7739	0.4011
managerial change	0.7539	0.4316
marketing of new products or processes	0.6437	0.5856
technology developed by others	0.6057	0.6331
Innovation amount, α= 0. 0.8075		
In the past 3 years, how innovative was the organization in terms of…		
new lines of products or services	0.9168	0.1595
changes in product or service lines	0.9168	0.1595
Technological leadership, α= 0.7782s		
The top managers of the organization favor…		
R&D, technological leadership, innovation	0.7893	0.3770
high-risk projects with chances of high returns	0.8776	0.2298
acting aggressively in the case of uncertainty	0.8449	0.2861
Competitive posture, α= 0.7192		
In dealing with its competitors, the organization typically is…		
initiating actions to which competitors respond	0.8188	0.3295
often the first to introduce new products/services	0.8510	0.2758
adopting a very competitive posture	0.7300	0.4672

Pioneer position, α= 0.8376		
Following the competitive strategy, the organization is…		
first to marker with new products/services	0.8892	0.1829
regularly produces state-of-the-art products/services	0.8063	0.2943
responds to early potential market signals	0.7118	0.3804
develops the best products/services in the industry	0.6844	0.4338
Process innovator, α= 0.7196		
Following the competitive strategy, the organization is…		
increases operating efficiencies	0.8596	0.2567
focuses on increasing productivity	0.834	0.2771
develops new process innovations to reduce costs	0.7877	0.314
produces products/services at a lower cost level	0.43	0.7607
Customer adapter, α= 0.7855		
Following the competitive strategy, the organization is…		
develops customer loyalty	0.8592	0.2293
tailors products/services to fit customers' needs	0.7743	0.3139
is flexible to quickly respond to customer needs	0.7352	0.3479

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.11: Results of the innovation cluster analysis.

Variable	Mean (SD)	Min	Max
Non-innovators, N = 355			
New or improved products/services	-0.60 (0.91)	-2.54	1.91
Resources invested in innovation	-0.66 (0.87)	-3.45	2.47
Risk-friendly, innovative management	-0.62 (0.94)	-2.16	2.68
Cutting edge compared to competitors	-0.78 (1.04)	-2.99	1.79
Innovation pioneer	-0.68 (0.78)	-2.55	1.29
Process innovator	-0.02 (1.10)	-4.33	2.65
Flexible customer adapter	-0.98 (1.05)	-4.14	1.95
Adapter, N = 418			
New or improved products/services	-0.79 (0.88)	-2.54	1.91
Resources invested in innovation	-0.56 (0.95)	-3.45	1.53
Risk-friendly, innovative management	-0.70 (0.75)	-2.16	2.68
Cutting edge compared to competitors	-0.46 (0.83)	-2.99	2.06
Innovation pioneer	-0.65 (0.79)	-3.04	1.92
Process innovator	-0.23 (0.97)	-2.87	2.31
Flexible customer adapter	0.50 (0.74)	-1.65	2.62
Small innovator, N = 526			
New or improved products/services	0.38 (0.64)	-1.80	1.91
Resources invested in innovation	0.24 (0.80)	-2.37	2.47
Risk-friendly, innovative management	0.17 (0.74)	-2.16	2.08
Cutting edge compared to competitors	0.11 (0.68)	-2.15	2.36
Innovation pioneer	0.00 (0.72)	-2.53	2.47

Process innovator	-0.09 (1.00)	-4.87	2.38
Flexible customer adapter	0.41 0(.70)	-1.99	2.38
Pioneer, N = 551			
New or improved products/services	0.67 (0.71)	-1.41	1.91
Resources invested in innovation	0.65 (0.77)	-1.79	2.47
Risk-friendly, innovative management	0.79 (0.74)	-1.65	2.68
Cutting edge compared to competitors	0.76 (0.76)	-2.42	2.36
Innovation pioneer	0.96 (0.64)	-0.97	3.08
Process innovator	0.30 (0.84)	-2.57	2.21
Flexible customer adapter	-0.08 (0.87)	-3.80	1.51

Notes: Including mean values of the factors, standard deviations in brackets, minimal and maximum values.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.12: Results of the factor analysis of market and firm indicators.

Variable	Factor	Uniqueness
Firm		
The current level of performance of the organization relative to your competitors for…		
customer retention	0.7343	0.4607
market share growth	0.7245	0.4751
rate of return on capital	0.6900	0.5239
employee productivity	0.6874	0.5275
TechMar		
The market is characterized by…		
products/services that are quickly obsolete	0.7406	0.4454
production/service technologies that change a lot	0.7227	0.4744
difficult predictions of actions of the competitors	0.6208	0.6016
difficult forecasts of consumer demands	0.5851	0.5768
frequently changing marketing practices	0.5024	0.7301
CompMar		
The market is characterized by…		
high concentration rate	0.7265	0.4689
difficulties, to find suitable labor	0.4742	0.7726
very high entry barriers	-0.6231	0.6103

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.13: Description of included variables in the regression equations.

Variables	Description	Code	(1)	(2)	(3)
Dependent variables					
Inno	Cluster of innovation factors	Grouped 1-4	x	x	
HRM practices					
HRM01	Training for new employees	1-7	x		
HRM02	Training for all employees	1-7	x		
HRM03	Cross-training	1-7	x		
HRM04	Mission communication	1-7	x		
HRM05	Communication procedures	1-7	x		
HRM06	Teamwork	1-7	x		
HRM07	Employee involvement	1-7	x		
HRM08	Suggestion reactions	1-7	x		
HRM09	Appraisals	1-7	x		
HRM10	Grievance procedure	1-7	x		
HRM11	Transparency	1-7	x		
HRM12	Performance reward	1-7	x		
HRM13	Team reward	1-7	x		
HRM14	Firm profit reward	1-7	x		
HRM15	Appraisal system	1-7	x		
Human resource management (HRM)					
Remuneration	HRM factor 1	Continuous		x	
Communication	HRM factor 2	Continuous		x	
Appreciation	HRM factor 3	Continuous		x	
Education	HRM factor 4	Continuous		x	
HRM regime 1	HRM regime cluster 1	Binary			x
HRM regime 2	HRM regime cluster 2	Binary			x
HRM regime 3	HRM regime cluster 3	Binary			x
HRM regime 4	HRM regime cluster 4	Binary			x
HRM regime 5	HRM regime cluster 5	Binary			
Control variables					
Firm	Firms' situation	Continuous	x	x	x
TechMar	Technological market	Continuous	x	x	x
CompMar	Competitive market	Continuous	x	x	x
Foreign	Not Australian owned	Binary	x	x	x
Size1	Size group	Binary	x	x	x
Size 2	Size group	Binary	x	x	x
Size 3	Size group	Binary	x	x	x
Size 4	Size group	Binary	x	x	x
Size 5	Size group	Binary			
Year	Year dummies	Binary	x	x	x
Sec	Sector dummies	Binary	x	x	x

Table 4.14: Marginal effects of the Ordered Probit regression, equation (3) and (4) using lagged values.

Variables	Non-innovator			Adapter			Small Innovator			Pioneer		
Equation (3)												
Lag Remuneration	-0.040	(0.003)	***	-0.016	(0.001)	***	0.010	(0.001)	***	0.045	(0.004)	***
Lag Communication	0.006	(0.003)	*	0.002	(0.001)	*	-0.001	(0.001)	*	-0.006	(0.004)	*
Lag Appreciation	-0.020	(0.003)	***	-0.008	(0.001)	***	0.005	(0.001)	***	0.022	(0.004)	***
Lag Education	-0.009	(0.003)	***	-0.004	(0.001)	***	0.002	(0.001)	***	0.011	(0.004)	***
N		107			120			154			127	
Chi²							186.56***					
L-L							-606.4092					
Pseudo-R2							0.1333					
Equation (4)												
Lag HRM Regime 1	0.059	(0.010)	***	0.018	(0.002)	***	-0.019	(0.004)	***	-0.058	(0.009)	***
Lag HRM Regime 2	-0.004	(0.010)		-0.002	(0.004)		0.001	(0.003)		0.005	(0.012)	
Lag HRM Regime 3	0.023	(0.012)	**	0.008	(0.004)	**	-0.007	(0.004)	*	-0.025	(0.012)	**
Lag HRM Regime 4	-0.019	(0.008)	**	-0.008	(0.004)	**	0.004	(0.002)	***	0.023	(0.010)	**
Lag HRM Regime 5	--	--		--	--		--	--		--	--	
N		107			120			154			127	
Chi²							179.5***					
Pseudo-R2							0.1283					
L-L							-609.94218					

Notes: Calculated using the Stata ado-file of Bartus (2005). Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %.
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.15: Correlations of the independent variables.

	HRM01	HRM02	HRM03	HRM04	HRM05	HRM06	HRM07	HRM08	HRM09	HRM10	HRM11	HRM12	HRM13	HRM14	HRM15
HRM01	1														
HRM02	0.61	1													
HRM03	0.38	0.47	1												
HRM04	0.32	0.37	0.24	1											
HRM05	0.40	0.45	0.32	0.62	1										
HRM06	0.36	0.39	0.36	0.46	0.51	1									
HRM07	0.31	0.41	0.34	0.42	0.46	0.53	1								
HRM08	0.31	0.41	0.35	0.44	0.47	0.46	0.68	1							
HRM09	0.36	0.39	0.26	0.45	0.49	0.39	0.38	0.40	1						
HRM10	0.33	0.30	0.15	0.35	0.40	0.27	0.28	0.27	0.47	1					
HRM11	0.37	0.39	0.31	0.44	0.43	0.37	0.38	0.42	0.56	0.52	1				
HRM12	0.21	0.30	0.30	0.35	0.28	0.34	0.36	0.41	0.42	0.14	0.39	1			
HRM13	0.20	0.23	0.29	0.27	0.25	0.40	0.30	0.32	0.28	0.09	0.28	0.61	1		
HRM14	0.14	0.18	0.19	0.25	0.22	0.26	0.27	0.33	0.27	0.09	0.26	0.55	0.64	1	
HRM15	0.27	0.26	0.23	0.42	0.39	0.36	0.33	0.37	0.57	0.28	0.44	0.65	0.50	0.51	1
Factor1	0.07	0.10	0.22	0.20	0.12	0.25	0.19	0.26	0.33	-0.03	0.26	0.81	0.82	0.82	0.71
Factor2	0.14	0.28	0.27	0.55	0.57	0.69	0.82	0.76	0.24	0.12	0.22	0.23	0.22	0.17	0.19
Factor3	0.30	0.26	-0.05	0.49	0.49	0.16	0.13	0.16	0.71	0.79	0.67	0.17	-0.01	0.04	0.45
Factor4	0.76	0.76	0.74	0.08	0.23	0.26	0.20	0.20	0.16	0.15	0.25	0.13	0.16	0.05	0.04
Reg 1	-0.24	-0.20	0.01	-0.31	-0.32	-0.12	-0.07	-0.10	-0.54	-0.57	-0.49	-0.09	-0.35	-0.08	0.05
Reg 2	-0.26	-0.28	-0.32	0.02	-0.04	-0.10	-0.09	-0.10	0.13	0.09	0.05	0.13	0.21	0.21	-0.12
Reg 3	0.08	0.07	-0.04	0.03	0.09	-0.05	-0.01	-0.04	0.00	0.21	0.02	-0.44	-0.34	-0.59	0.04
Reg 4	0.22	0.19	0.12	-0.12	-0.07	-0.16	-0.22	-0.18	0.09	0.08	0.13	-0.03	0.05	0.02	-0.37
Reg 5	0.33	0.35	0.30	0.36	0.37	0.40	0.36	0.39	0.35	0.27	0.36	0.30	0.36	0.29	0.33
Firm	0.16	0.20	0.18	0.22	0.20	0.21	0.22	0.30	0.19	0.12	0.21	0.30	0.23	0.22	0.22
TechMar	0.06	0.07	0.13	0.13	0.11	0.13	0.12	0.14	0.11	0.03	0.12	0.17	0.16	0.14	0.13
CompMar	-0.11	-0.16	-0.09	-0.12	-0.13	-0.08	-0.11	-0.10	-0.15	-0.22	-0.13	-0.06	-0.05	-0.06	-0.08
Foreign	0.03	0.00	0.01	-0.04	0.01	-0.02	-0.01	-0.03	0.07	0.00	0.05	0.09	0.11	0.21	0.10

Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.16: Correlations of the independent variables.

	Factor1	Factor2	Factor3	Factor4	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Firm	TechMar	CompMar	Foreign
Factor1	1												
Factor2	0.060	1											
Factor3	0.01	0.00	1										
Factor4	0.00	0.04	-0.02	1									
Reg 1	-0.71	-0.02	-0.71	-0.02	1								
Reg 2	0.22	-0.43	0.22	-0.43	-0.40	1							
Reg 3	0.19	0.08	0.19	0.08	-0.20	-0.26	1						
Reg 4	0.15	0.29	0.15	0.29	-0.19	-0.24	-0.12	1					
Reg 5	0.24	0.25	0.24	0.25	-0.28	-0.37	-0.18	-0.17	1				
Firm	0.23	0.21	0.10	0.13	-0.08	-0.05	-0.03	-0.04	0.20	1			
TechMar	0.17	0.13	0.03	0.05	-0.04	0.03	-0.07	-0.03	0.08	0.04	1		
CompMar	-0.02	-0.06	-0.18	-0.10	0.14	0.00	-0.09	-0.02	-0.06	-0.08	-0.03	1	
Foreign	0.18	-0.09	0.03	0.01	-0.05	0.09	-0.14	0.04	0.02	-0.06	0.10	0.05	1

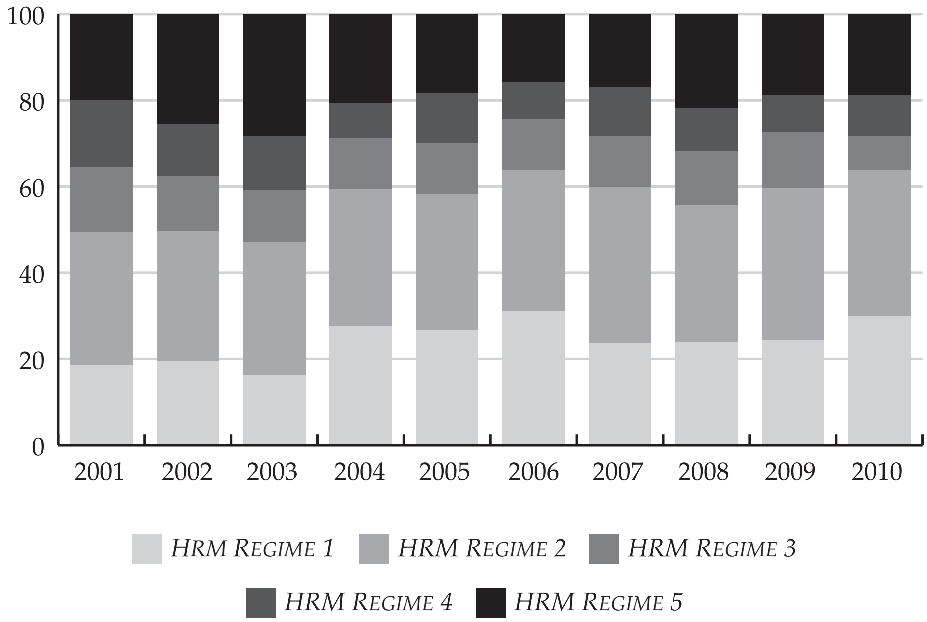
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Table 4.17: Mean and standard deviation of the additional control variables.

Variable	N	Mean	Std. Dev.
Factor1	1991	$-5.26e^{-13}$	1
Factor2	1991	$-1.01e^{-09}$	1
Factor3	1991	$-3.13e^{-10}$	1
Factor4	1991	$9.02e^{-10}$	1
Reg 1	1991	0.2411	0.4278
Reg 2	1991	0.3245	0.4683
Reg 3	1991	0.1226	0.3280
Reg 4	1991	0.1085	0.3111
Reg 5	1991	0.2034	0.4026
Firm	1788	$-2.23e^{-09}$	1
TechMar	1918	$-3.76e^{-11}$	1
CompMar	1918	$3.35e^{-10}$	1

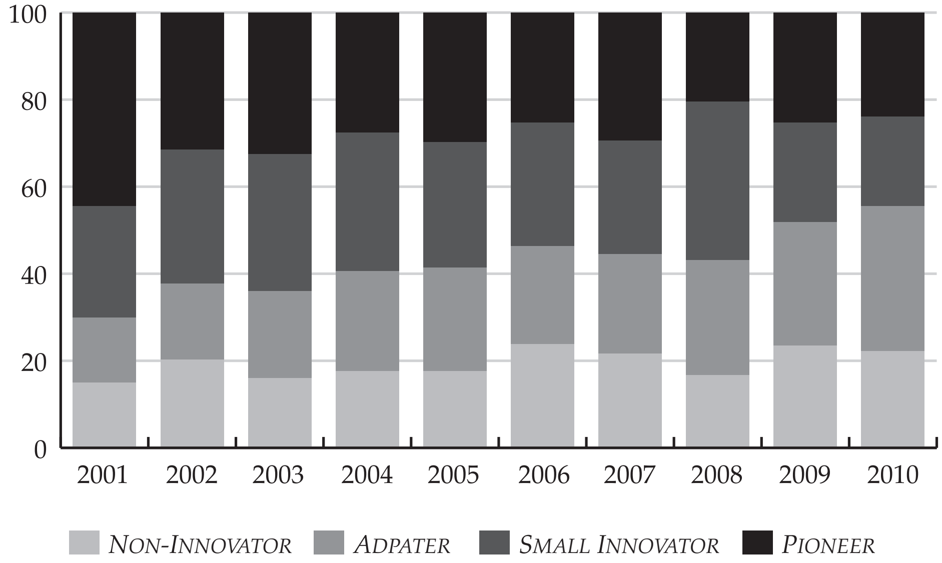
Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Figure 4.5: Occurrence of the HRM regimes over the years 2001-2010.



Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

Figure 4.6: Occurrence of the innovation clusters over the years 2001-2010.



Source: Melbourne Institute Business Survey, 2001-2010. Own calculations.

5 Skill-biased labor demand
Technological or organizational resasons?

The content of this paper refers to skill-biased labor demand in manufacturing and service sectors in Western Germany and the question of whether it is driven by technological or by organizational changes. The incidence of skill-biased technological change is often held to be responsible for the increasing demand for skilled labor, based on the assumption that new technologies prefer higher skills. Evidence of skill-biased technological change has been found in several empirical studies, especially using data from Anglo-Saxon countries. However, organizational changes as a cause for skill biases have not received as much attention. Using German data from 1993 to 2008 with linked information on employer and employee level, I analyze changes in the share of highly skilled employees in the total employment. In addition to technological changes, I also account for organizational changes. It turns out that skill-biased technological and organizational change can be found in manufacturing sectors, while the changes in the employment demand in service sectors can rather be attributed to technological than to organizational changes.

5.1 Introduction

Since the last 30 years, an increasing demand for high-skilled employees in almost all developed countries can be observed. Thereby, not only the number of employees, but also their wages has risen strongly compared to low-skilled employees. The economic literature sees a connection between these developments and technological changes (e.g. Autor et al., 1998 or Machin and Van Reenen, 1998). It is assumed that new technologies prefer highly educated employees, so that the demand on the labor market is biased in the direction of skills. In addition, technological changes allow to replace uneducated workers, which exacerbates the inequality. This so-called skill-biased technological change (SBTC) is considered to be the reason for the increasing demand and wage level for high-skilled workers (Machin, 2002: 2).

However, a second approach has been discussed recently. Besides technological changes, major organizational changes within the companies are recognizable since the last two decades. Following Bresnahan et al. (2002) or Piva et al. (2005), rather skill-biased organizational change (SBOC) explains the increasing demand for highly educated employees. However, the thesis has received less attention in most of the previous studies.

This paper analyzes both, SBTC and SBOC to explain the changed labor demand using an employer-employee level dataset of establishments in Western Germany from 1993 to 2008. Unlike many previous studies, manufacturing and services sectors are considered, which I analyze separately. The share of services in Germany has grown increasingly. Especially services that are classified as knowledge-intensive, such as research, consulting or telecommunication, make an increasing contribution to innovation activities (Cordes and Gehrke, 2012). The results prove the evidence of SBTC in both sectors, although organizational changes have a greater influence than technological changes in manufacturing sectors.

The rest of the paper is structured as follows. Chapter 5.2 examines the incidence of changes in the demand for high-skilled employees as well as the definition of SBTC and SBOC. Chapter 5.3 reviews some previous empirical studies. The theoretical model is explained in Chapter 5.4. The data and the underlying empirical model are presented in Chapter 5.5 and 5.6, respectively. Chapter 5.7 gives the results, before Chapter 5.8 summarizes some conclusions.

5.2 Skill-biased labor demand

Within the last 30 years, labor market inequalities between skilled and unskilled employees have increased significantly. First, the employment demand has shifted in favor of skilled workers. Second, a strong increase in the differences of relative wages can be observed. This is particularly true for Anglo-Saxon states, such as the United States (US) and the United Kingdom (UK). The supply as well as the relative wages of highly educated workers in the US and the UK has risen sharply, as shown by Berman et al. (1998: 1245). In contrast, the unemployment among unskilled or only low-skilled workers in the US rose sharply and remained at a high level (OECD, 1992; Machin, 2002). Bound and Johnson (1995) also indicate decreasing wages for unskilled workers in the US. While the wage changes in the US and the UK are the strongest, this trend cannot be found in other European countries (Machin, 2002: 3).[1] However, an increase in the employment of skilled employees in almost all countries can be recognized (Berman et al., 1998: 1245; Machin, 2002: 3).[2]

In addition to wage changes and the influence of international trade, mainly two theses are discussed to be responsible for these developments. First and most important, technological changes are recognized most often as a cause of these inequalities. Simultaneously with the increased inequality in employment and wages between skilled and unskilled employees, strong technological changes have occurred. It is assumed that the use of the new technologies requires a certain level of skills. In addition, the new technologies can replace the work of low-educated employees. They act like substitutes, while highly skilled employees and new technologies are considered to be complements. For this reason, the demand as well as

1 For specific information on wage development in the US see Katz and Murphy (1992). A summary of changes in the US and other OECD countries can be found in Katz and Autor (1999).

2 See also Freeman and Katz (1994), Murphy et al. (1998), Katz and Autor (1999) or Dustmann et al. (2009). Trends in the income distribution are shown by the OECD (1996: 61-62) from 1979 to 1995. An overview of the wage developments from the 1970s to the 1990s in a variety of countries can be found in Sanders and Ter Weel (2000: 44).

the wage level for high-skilled employees increases. In contrast, the demand and the wages for low-skilled workers decrease. In that case, technological change is biased towards skills (Krueger, 1993; Machin and Van Reenen, 1998). The consistently increased use of computers since the 1980s is often cited as an evidence of this hypothesis, as used by e.g. Krueger (1993) or Autor et al. (1998).

SBTC is not new. A similar development was already apparent at the beginning of the last century (Goldin and Katz, 1995, Acemoglu, 2002). In the years from 1910, the demand for qualified employees has clearly risen in some industries. As stated by Goldin and Katz (1998: 695), many tasks of unskilled workers were replaced by the introduction of electricity. According to these developments, Griliches (1969) argued for a complementarity between skills and capital. In addition, several researchers back in the 1960s and 1970s years, such as Nelson and Phelps (1966) or Schultz (1975), assumed a positive relationship between technological change and the demand for skills. However, a bias towards higher skills seems to be a phenomenon of the 20th century (Acemoglu, 2002: 8). Following Bresnahan et al. (2002) or Goldin and Katz (1998), technological change in the 19th century and early 20th century has been rater skill-replacing. One example is the development of weaving machines. In fact, these machines were easy to use by uneducated employees and certain skills became obsolete after their introduction.[3] So where is the difference between the 19th and the 20th century? Following Acemoglu (2002: 9), the development of new technologies always depends on possible profits and is therefore based on the current supply on the labor market. The 19th century has been characterized by a high supply of uneducated employees, resulting in skill-replacing technological changes. Due to the increasing number of highly educated employees, the effect is exactly the other way around in the 20th century. However, today's technological changes also not necessarily require higher skills. In many areas, the introduction of computers has simplified complex working processes (Acemoglu, 1998: 1056). Following Acemoglu (2002: 7), the increasing skill bias in recent years is not based on a rising rate, but rather on a new design of technological changes.

3 More examples are given by Acemoglu (1998: 1056).

However, a second and more recent approach tries to explain the increasing skill demand. Following the thesis of skill-biased organizational change (SBOC), rather organizational than technological changes within the companies are held to be responsible. The thesis of SBOC is based on the changes in organizational structures within companies, which can be observed since the last 20 years. Based on the classical organization theory of Taylor (1917), tasks are divided according to their function and processed in different departments. Following the basic work of Chandler (1962) and more recently Lindbeck and Snower (1996), this segmentation is increasingly replaced by a more open and holistic form of organization including methods such as teamwork, quality controls, enhanced responsibilities and multi-tasking. The changed organizational practices such as the extension of working tasks or decision levels require appropriately skilled employees, resulting in the fact that organizational changes are biased towards skills. As stated by Caroli (2001), the skill upgrading can be more attributed to both, technological and organizational changes. The technological changes of the last decades mostly implicated also organizational changes. Following Aghion et al. (1999), technological changes can also lead to subsequent organizational changes. Therefore, both approaches are not necessarily independent. Rather, technological and organizational changes can affect each other and commonly increase the bias (Piva et al., 2005: 144).

5.3 Literature review

The question of whether technological change is the reason of the increasing demand for skills has already been investigated several times. An overview of previous studies can be found in Chennells and Van Reenen (1999), Sanders and Ter Weel (2000) or Piva et al. (2005). The previous studies differ in particular with regard to the dependent variable, the aggregation level as well as the proxy used to measure technological progress. The difference in the share of high-skilled employees in the total employment or in the wage bill serves as dependent variables. As a source of technological change, the expenditures for R&D are used in most of all studies. Furthermore, the number of patents, the use of computers or improved technologies or the successful implementation of innovations can be found as technology proxies.[4] One of the most famous studies of SBTC is the work of Berman et al. (1994). Using US manufacturing data at industry level, they find a significant positive influence of investments in R&D and computers on the increased share of high-skilled employees in total employment and in the wage bill. Autor et al. (1998) confirm these results for other sectors beyond manufacturing with the help of an extended dataset. Adams (1999) analyzes SBTC at company level in the US chemical sector. His results prove the evidence of SBTC at firm level using the flow of R&D and the stock of research knowledge per company and per industry as well as spillovers as technology variables.

Machin and Van Reenen (1998) expand the industry level analysis comparing the results of US sectors with those from six other OECD countries. A positive and significant correlation of R&D intensity and skills can be found in all countries. The same is shown by Berman et al. (1998). Their results demonstrate the evidence of SBTC in developed countries, proving that SBTC is not a national phenomenon. Following Berman and Machin (2000), this is true for developed and emerging, so-called medium-income countries. The results of Gera et al. (2001) provide evidence of a SBTC in Canadian industries. Following his results, R&D intensity as well as the share of technicians can explain the increasing share of high-skilled employees in total employment and in the wage bill. The results of Machin (1996) show a positive influence of research intensity and innovation on the skill level using UK industry level data. Hansson (1996) finds evidence of SBTC in Swedish manufacturing industries. Duguet and Greenan (1997) use a panel dataset of French manufacturing companies. They analyze the influence of different types of innovation and demonstrate that the decreasing demand for low-skilled employees can mainly be attributed to the development of new products. Distinguishing between three categories of employment change, Kaiser (2000) analyze the business-related service sector in Germany. The results show positive and significant effects of technology investments on the demand for high- and medium-skilled employees. A similar analysis for the

4 However, Chennells and Van Reenen (1999: 18-19) point to potential endogeneity problems caused by reverse causality between technology variables and skill composition. Especially the use of computers as technology proxy is questionable. More information can be found in DiNardo and Pischke (1997).

German manufacturing and service sectors is given by Kölling and Schank (2003). The results indicate that the developments can be mainly attributed to the wage structure. Although technological changes in the service sector reduce the demand for low- and medium-skilled employees, the influence on highly skilled employees, especially in the manufacturing sector, is not significant. Although the evidence of SBTC can be found in several countries, the results for other countries are generally not as strong as in North America or the UK (Piva et al., 2005: 144).

Following the SBOC thesis, the increasing demand for high-skilled employees may be primarily attributed to organizational changes. Caroli and Van Reenen (2001) work with both, French and British data with computer use as technology proxy. Their results differ depending on the country. While only the data of British companies clearly confirm SBTC, both datasets show a negative influence of organizational changes on low-skilled employees. The analysis proves that organizational changes make a significant contribution in order to explain the skill-upgrading. Similar results are found by Greenan (2003). Following her results, the increased demand for skills in French companies is much more correlated with organizational than with technological changes. Bellmann et al. (2002) also demonstrate an association between technological and organizational changes in Germany. SBTC can weakly be confirmed, while low-skilled employees and organizational changes act as substitutes. Bresnahan et al. (2002) analyzes the impact of technological and organizational changes on the demand for skilled employees using firm-level data from the US. It turns out that technologies combined with organizational changes have a greater influence than technology changes alone. Piva et al. (2005) shows that the growing demand for skills in Italian manufacturing companies can also rather be attributed to organizational changes. In addition, it is shown that in particular a common effect of both changes exists, which has been little considered yet.

5.4 Theoretical model

The theory of SBTC is mainly based on the assumptions of Hicks (1932). In his theory of neutral technical change, Hicks believes that the relative prices of capital and labor can create an incentive to innovate. As a consequence of innovation, the more expensive input factor can, at least partially, be saved. This can also be transferred to skills.

Analogous to Sanders and Ter Weel (2000: 1-2), I consider a single sector. Labor is regarded as the only input factor, divided into high- and low-skilled workers, L_H and L_L. Thereby, L_H and L_L are imperfect substitutes and differ in terms of quality and costs. The workers are assumed to be risk neutral and profit maximizing. The production function with constant elasticity of substitution (CES), as developed by Arrow et al. (1961), is given by

$$Y = [(\theta_L L_L)^\rho + (\theta_H L_H)^\rho]^{1/\rho} \quad , \tag{1}$$

for every time period t with L_L and L_H as the supply of low- and high-skilled labor and $0<\rho<1$. θ_H and θ_L reflect the potential technological progress of the input factors. The elasticity of substitution between L_L and L_H in (1) is given by $\sigma=1/(1-\rho)$. An elasticity of $\sigma>0$ or $\rho>0$ means that skilled and unskilled workers are substitutes. An increase in the demand for skilled employees leads to a decrease of the demand for unskilled employees. If $\sigma=\infty$, skilled and unskilled workers would be perfect substitutes. $\sigma<0$ or $\rho<0$, in contrast, represents both groups as complements. In that case, an increase in the demand for skilled employees also leads to an increasing demand for unskilled employees.[5]

The costs for the two input factors correspond to the wages for high- and low-skilled workers, w_H and w_L. Considering a perfectly competitive labor market, the factor labor is paid according to its marginal productivity

$$w_H = \frac{\partial Y}{\partial L_H} = \theta_H{}^\rho L_H{}^{\rho-1} \quad \text{and} \quad w_L = \frac{\partial Y}{\partial L_L} = \theta_L{}^\rho L_L{}^{\rho-1} \quad . \tag{2}$$

5 Two extremes can occur. If $\sigma \to 0$ or $\rho \to -\infty$, (1) will be a Leontief production function and the production factors skilled and unskilled workers are used in a fixed proportion. If $\sigma \to 1$, the production function Y is a Cobb-Douglas function.

The partial derivatives for both groups result in

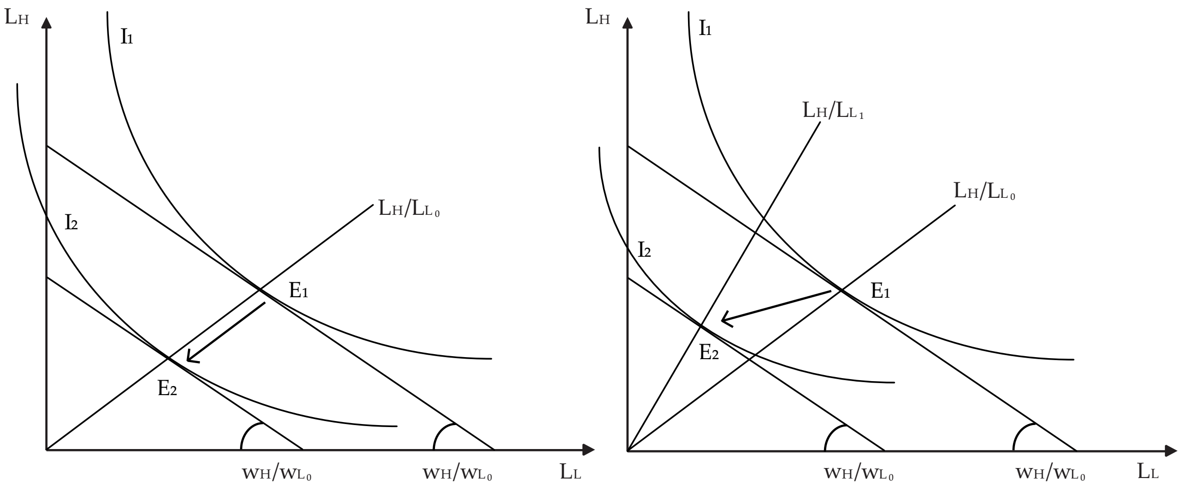
$$w_H = [(\theta_H L_H)^\rho + (\theta_L L_L)^\rho]^{(1-\rho)/\rho} \cdot \theta_H^{\ \rho}\ \theta L_H^{\ \rho-1}$$
$$w_L = [(\theta_H L_H)^\rho + (\theta_L L_L)^\rho]^{(1-\rho)/\rho} \cdot \theta_L^{\ \rho}\ \theta L_L^{\ \rho-1} \quad . \tag{3}$$

In the profit-maximizing equilibrium, the factor price ratio has to be consistent with the marginal productivities. In this case, the factor ratio equals the ratio of wages of skilled and unskilled labor. The ratio of the partial derivatives in (3) is given by

$$\frac{w_H}{w_L} = \left[\frac{\theta_H}{\theta_L}\right]^\rho \left[\frac{L_H}{L_L}\right]^{\rho-1} \quad . \tag{4}$$

It is assumed that technological progress increases the productivity of either skilled θ_H or unskilled θ_L labor. It allows growth even with constant factor use. Technological progress is neutral in the sense of Hicks if the relative factor prices in (4) remain constant in a growing productivity. In this case, θ_H and θ_L change proportionally. In contrast, a bias is existent if one of the two parameters is growing faster than the other one. If the factor-saving technological progress θ_H is higher than θ_L, the technological progress is biased against low-skilled workers and vice versa. Figure 5.1 shows the changed input factor ratio after a neutral and a biased technological change.

Figure 5.1: Skill-neutral and skill-biased technological change.



As a consequence of an innovation, the isoquant I_1 shifts to the origin to I_2. The same output can be produced with lower factor input. Neutral technological change in the sense of Hicks means that even after the innovation the ratio of the input factor remains the same. The equilibrium moves from E_1 to the new equilibrium E_2, but the ratio L_H/L_L remains the same. In the case of a bias towards high-skilled labor, the ratio L_H/L_L changes and the equilibrium moves to E_3. After the technological progress, the use of high-skilled workers L_H decreases less than the use of low-skilled employees L_L. In that case, the wage ratio is constant. The same applies for a change of the wage ratio if the factor ratio remains constant (Sanders and Ter Weel, 2000: 5).

Considering several sectors, these results are not necessarily still valid. A biased labor demand may be caused by changes within or also between the various sectors. Considering the one-sector equation (1) aggregated for multiple sectors *j*

$$Y_j = A_j [(\theta_{Lj} L_{Lj})^\rho + (\theta_{Hj} L_{Hj})^\rho]^{1/\rho} \quad , \tag{5}$$

with A_j as a factor neutral technological progress in sector *j*. The labor demand is given by the profit maximization of the individual sectors for given wages. Hence, a demand function for high- and low-skilled labor for each industry is given by

$$\begin{aligned} w_{Hj} &= P_j A_j [(\theta_{Hj} L_{Hj})^\rho + (\theta_{Lj} L_{Lj})^\rho]^{(1-\rho)/\rho} \cdot \theta_{Hj}^{\ \rho} \ \theta L_{Hj}^{\ \rho-1} \\ w_{Lj} &= P_j A_j [(\theta_{Hj} L_{Hj})^\rho + (\theta_{Lj} L_{Lj})^\rho]^{(1-\rho)/\rho} \cdot \theta_{Lj}^{\ \rho} \ \theta L_{Lj}^{\ \rho-1} \end{aligned} \quad . \tag{6}$$

Under the assumption of perfect mobility of labor, similar workers receive similar wages in all sectors (Sanders and Ter Weel, 2000: 6). Hence, the wage ratio for all sectors is given by

$$\frac{w_H}{w_L} = \left[\frac{\theta_{Hj}}{\theta_{Lj}}\right]^\rho \left[\frac{L_{Hj}}{L_{Lj}}\right]^{\rho-1} \quad . \qquad j = 0,1,\ldots,k \tag{7}$$

At a constant wage ratio, technological progress is factor neutral in the sense of Hicks if θ_{Hj} or θ_{Lj} does not change the employment ratio L_{Hj}/L_{Lj}. However, the aggregate demand may be skill-biased, although the technical progress within each sector is neutral. Skill bias at the aggregate level can also be attributed to different levels of neutral technological changes within the individual sectors.[6]

Based on the theory and the results of previous studies, the increasing demand for high-skilled employees can be attributed to skill-biased technological change. Therefore, the following hypothesis can be derived.

[6] A detailed derivation is given in Sanders and Ter Weel (2000: 6-7).

Hypothesis I The technological change in Western Germany is biased towards high-skilled and against low-skilled employees.

In contrast, organizational changes can also be responsible for the changing skill demand. According to the results of Bresnahan et al. (2002) and Piva et al. (2005), technological and organizational changes often occur together.

Hypothesis II Organizational changes also have an influence on the changing demand for skills, also in combination with simultaneously occurring technological changes.

Finally, technological and organizational changes can lead to a different relationship between capital and labor, i.e. as complements or as substitutes.

Hypothesis III High-skilled workers and capital are complements, while low-skilled workers and capital act as substitutes.

The data as well as the empirical model to test the hypotheses are presented in the following chapters.

5.5 Data

The data basis of this paper is the cross-sectional model, version 2 from 1993 to 2008 of the Linked Employer-Employee Data (LIAB) from the Institute for Employment Research (IAB). The data access was carried out by a guest stay at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) and a subsequent controlled remote data processing at the FDZ.[7] The LIAB is a combination of the IAB Establishment Panel (IABB) and the employment data from the Federal Employment Agency (BA). Containing data on employer and employee level, the LIAB allows analyzing both, the supply and the demand on the German labor market. The personal information stem from the Integrated Employment Biographies (IEB), consisting of all persons belonging to the group of employees subject to so-

7 Further information on the individual datasets, the included variables as well as the data quality and potential linkage problems can be found in Jacobebbinghaus (2008).

cial insurance, marginal employees, job applicant or social benefit recipients at least once during the observation period. The datasets are linked using an establishment identification number. The linkage can be subject to potential sources of error (Jacobebbinghaus, 2008: 26-28). The identification numbers may change over time and personal information could partially be linked to the wrong business unit. In some cases, multiple business units are listed under the same number. While the establishment data stem from the individual surveyed unit, the employee's information refers to all units under this number. In order to minimize potential errors, the wave labeling is used to control whether every observation still matches with the observation of the first interview. In addition, I do not consider any information of employees with employment duration of less than one month. The meaning of the turnover variable in the dataset is not unambiguous. The variable can include the turnover, the total assets, the total premiums paid or the budget volume. Due to deviations in the meaning of turnover, the banking and insurance industry, the sectors of education, health and social services as well as non-profit organizations and observations of the public administration are excluded. All monetary variables are given in Euro (€). Due to the fact that companies from Eastern Germany are only surveyed since 1996 and distortions in the classification of the skill level may arise, the analysis is limited to data from Western Germany.

I use several variables to define the skill groups in this paper. The distinction between blue- and white-collar workers is not significantly relevant for service sectors. In addition, the skills are not consistently reflected by education.[8] In addition to school and further education, the dataset provides information on the qualification, the applied occupation and the position within an establishment. Thus, work experience can be considered as well. However, each establishment may classify the level of education in a different way. In addition, experience is also gained during employment, resulting in the increase of employee's skills. In order to control

[8] Skilled and unskilled workers are often solely distinguished by their school graduates. Thereby, skills and higher education are considered equal. As mentioned among others by Acemoglu (2002: 18), education and skills, however, are not perfectly correlated. Information on the complexity to define skills see e.g. Esposto (2008) or Toner (2009). Following the polarization hypothesis of Autor et al. (2003, 2006), SBTC is particularly relevant for medium-skilled employees. Due to the difficulties with the definition of the skill levels, the approach is not considered here, but is certainly interesting for future research, especially for SBOC.

for potential inconsistencies over time and to correct for missing values, I impute values for the education variables according to Fitzenberger et al. (2006). First, the education is used to classify the employees as skilled or unskilled. All observations without completed education, with a lower secondary, qualified lower secondary or intermediate school leaving certificate are classified as low-skilled. Second, information on position and qualification are considered. Therefore, low-skilled employees include assistants, unskilled workers and employees on vocational training. In contrast, observations with a completed high school degree and vocational training, as well as observations with university degree or a completion of a university of applied sciences belong to the group of high-skilled employees. The same applies to employees whose qualifications are specified as top executives, employees at the level as a university or technical college degree or as skilled workers (Toner, 2009: 11-14).

The wages as daily rates are censored. Incomes below the minimum threshold are not recorded until the year 1999. In addition, the charges are also right-hand censored in all years. The daily rates are only listed up to the upper income threshold specified in the pension scheme.[9] Therefore, I previously calculate a Tobit regression and use the results to estimate the daily wages. Information about gender, nationality, age, marital status and working hours serve as explanatory variables.[10] The estimates are made separately for the individual skill groups in every year. Afterwards, the median of the predicted wage variable is calculated per establishment for each skill group separately.[11] The estimated wages can assumed to be exogenous, so that potential endogeneity problems are eliminated.

Table 5.1 summarizes some descriptive statistics. Technological changes, measured by investments in information and telecommunication technology (ICT), take place in more than 50 percent of the establishments between 1993 and 2008. The share of establishments that have carried out organizational changes is even slightly higher. The changes can refer to changed methods of production, areas of operation, distri-

9 The income thresholds correspond to the information provided by the IAB.
10 As an example, the coefficients of the Tobit regression from 2000 can be found in Table 5.4 in the appendix.
11 The procedure is analogous to that of Kölling and Schank (2003).

bution channels or responsibilities as well as to the introduction of practices such as group work, result analysis, quality assurance or measurements related to the environment. Civil works as well as transportation and trade services are the most common sectors. About half of all observations belong to the manufacturing industry. However, the share is significantly higher considering establishments with organizational changes.

Table 5.1: Summary of descriptive statistics, percentage.

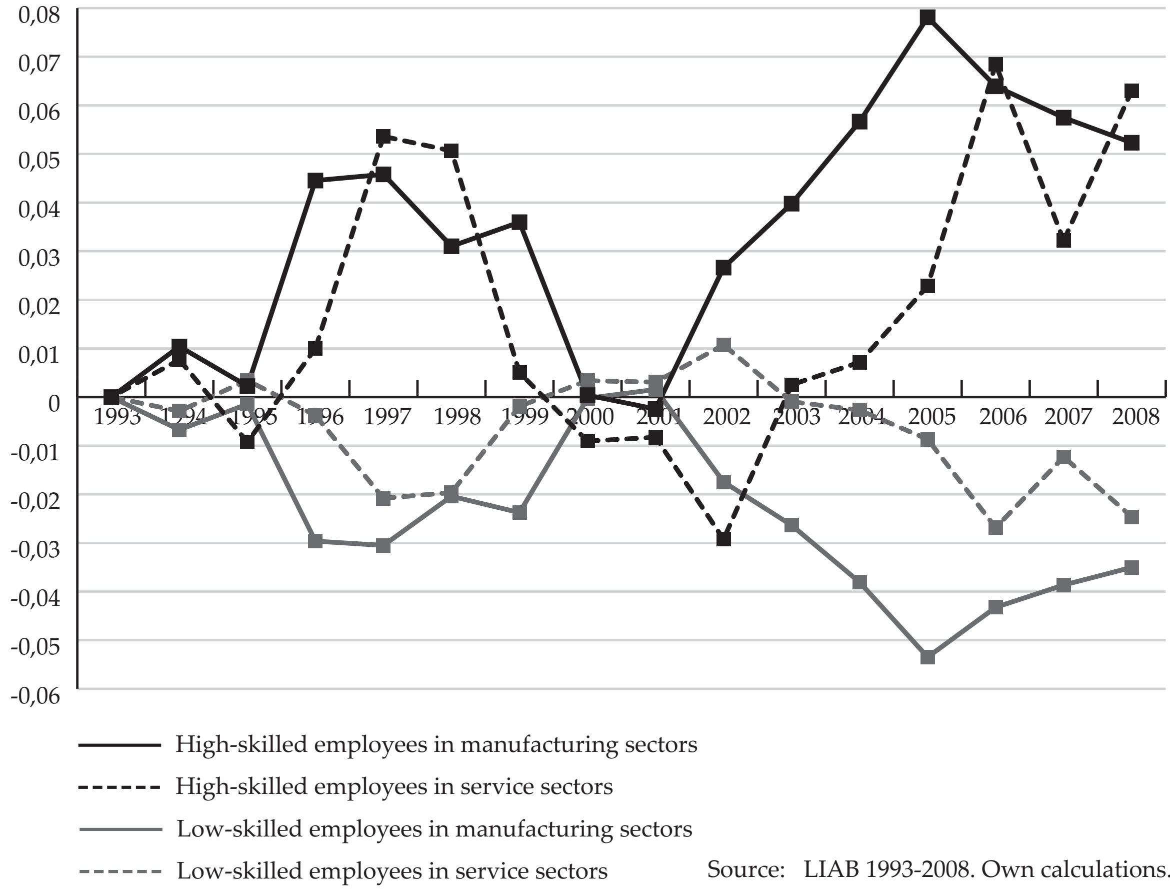
	All	Technological change	Organizational change
Technological change	51.07		
Organizational change	53.11		
Technological and organizational changes	46.88		
Sectors			
Agriculture	2.12	1.66	1.74
Nutrition	4.07	3.86	4.00
Consumer goods	5.39	5.64	6.00
Producer goods	9.13	10.27	12.2
Investment goods	17.93	20.79	25.58
Civil works	10.32	9.14	7.01
Trade	20.34	18.99	17.89
Transportation	5.85	5.42	5.47
Hotels and restaurants	4.60	2.70	2.95
Business services	15.02	17.30	12.60
Other services	5.23	4.22	3.96
Total	100.00	100.00	100.00
Grouping sectors			
Manufacturing sectors	51.05	51.37	57.13
Service sectors	48.95	48.63	42.87
Total	100.00	100.00	100.00
Employment size			
Less than 10	33.58	24.68	17.64
10 to under 25	16.22	15.98	13.97
25 to under 50	11.62	12.58	12.45
50 to under 250	21.59	25.57	28.72
250 and more	16.99	21.19	27.23
Total	100.00	100.00	100.00

Source: LIAB, 1993-2008. Own calculations.

50 percent of the establishments have less than 25 employees, while more than 45 percent of the establishments with technological changes and even more than 55 percent

of the establishments with organizational changes will have up to 250 employees. Figure 5.2 shows the development of the logged shares of high- and low-skilled employees in the total employment compared to the year 1993, separately for manufacturing and service sectors.

Figure 5.2: Logged shares of high- and low-skilled employees in the total employment compared to the year 1993.



Source: LIAB 1993-2008. Own calculations.

During the entire observation period, the share of high-skilled employees rises in both, the manufacturing as well as the service sectors. However, a decreasing share can be recognized from 1997 to 2001. In contrast, the share of low-skilled employees decreases from 1993 to 2008 in manufacturing and service sectors, although the decrease is less than the increase of educated workers. Compared to the manufacturing sector, the development of the services is delayed.

5.6 Empirical model

A transcendental logarithmic, so-called translog, model is used for the empirical estimation. Based on the work of Christensen et al. (1973), this approach is a flexible and simple representation of the frontier of the production technology. Thereby, the natural logarithm of costs is set up as a function of the logarithm of input prices, output and the incidence of technological or organizational changes, as given by

$$C_i[log\ (Y_i),\ log\ (K_i),\ log\ (w_{Hi}),\ log\ (w_{Li}),\ Tech_i,\ Org_i]. \tag{8}$$

In this case, K_i, Y_i, $Tech_i$ and Org_i are capital stock, output as well as technological and organizational changes, respectively. The prices of the input factors w_{Hi} and w_{Li} are the wages for low- and high-skilled employees. Using this cost function, individual cost share functions for the different skill groups can be derived as given in (9).

$$\begin{aligned} Share_{Hi} &= \alpha_{Hi} + \beta_{H1} log\ (Y_i) + \beta_{H2} log\ (K_i) + \beta_{H3} log\ (w_H/w_L)_i + \beta_{H4} Tech_i + \beta_{H5} Org_i + \varepsilon_{Hi} \\ Share_{Li} &= \alpha_{Li} + \beta_{L1} log\ (Y_i) + \beta_{L2} log\ (K_i) + \beta_{L3} log\ (w_L/w_H)_i + \beta_{L4} Tech_i + \beta_{L5} Org_i + \varepsilon_{Li} \end{aligned} \tag{9}$$

Under the assumption that the equations are independent of the error terms ε_{Hi} and ε_{Li}, the equation system can be estimated in a seemingly unrelated regression (SUR).[12] Proposed by Zellner (1962), the SUR approach assumes correlated error terms within an establishment, but not between companies. That means in this case, ε_{Hi} and ε_{Li} are correlated. An estimation using the SUR procedure is more efficient than the separate calculation by Ordinary Least Squares (OLS).[13] Following my first hypothesis of skill-biased technological change, the influence of technological changes captured in $Tech_i$ act in different directions for high- and low-skilled employees, i.d. β_{H4}>0 and β_{L4}<0. The second hypothesis refers to organizational changes, given by Org_i. Organizational changes are skill-biased, if β_{H5}>0 and β_{L5}<0. According to the third hypothesis, high-skilled employees and capital are complementary if β_{H1}>0. In contrast, low-skilled employees and capital are substitutes if β_{L1}<0 (Goldin and Katz, 1998).

The share of high- and low-skilled employees in the total employment, *S_HEmp* and *S_LEmp*, are used as dependent variables. According to equation (9), the following explanatory variables are used. The output is measured by the logarithm of the

12 Valid under the assumption of Sheppard's lemma and linear price homogeneity as in Adams (1999). A detailed derivation is given in Sanders and Ter Weel (2000: 20-22) .

13 Similar approaches are used by e.g. Berman et al. (1994), Betts (1997) or Machin and Van Reenen (1998).

turnover in the previous year *Turn*. Due to the relation to the turnover in the previous year, potential problems with endogeneity are assumed to be small. The logged sum of all investments in the past two years serves as a proxy for the capital of an establishment *Cap* (Kölling and Schank, 2003). The wage ratio is given by *R_HWage* and *R_LWage* for high- and low-skilled employees, respectively. The variable *Exp* measures the share of exports in the turnover and controls for the influence of international trade on the demand for skills. *InvICT* is a binary variable to identify establishments with investments in ICT and is used to describe the technology behavior of an establishment. The choice of this variable is also based on the fact that the use of ICT is also relevant for service sectors, while R&D expenditures are much more important for manufacturing sectors (Kaiser, 2000: 468). *Org* is used to control for changes within the establishments' organization. The binary coded variable is equal to one if any organizational changes within an establishment were made during the previous year. In order to account for the different developments in the sectors, I calculate the equations separately for manufacturing and service sectors. Finally, dummies for the years *Year* are included. Equation (9) can be written as

$$\begin{aligned} S\_HEmp = {} & \alpha_{Hi} + \beta_{H1}\, Turn + \beta_{H2}\, Cap + \beta_{H3}\, R\_HWage + \beta_{H4}\, Exp + \beta_{H5} InvICT + \beta_{H6} \\ & Org + \beta_{H7}\; Year + \varepsilon_{Hi} \\ S\_LEmp = {} & \alpha_{Hi} + \beta_{L1}\, Turn + \beta_{L2}\, Cap + \beta_{L3}\, R\_LWage + \beta_{L4}\, Exp + \beta_{L5} InvICT + \beta_{L6}\, Org \\ & + \beta_{L7}\, Year + \varepsilon_{Hi} \end{aligned} \tag{10}$$

In particular the changes of the shares are to be explained. Therefore, I use the differences of the variables in equation (10) indicated by *D_*. Equation (10) might cause a problem with reverse causality between technology or organizational indicators and skill upgrading. It can be argued that the increased use of high-skilled employees increases the probability of innovation. Similarly, the increasing demand for highly educated employees may be responsible for organizational changes. In order to account for a possible reverse causality, the incidence of technological and organizational change in the period before the difference, $InvICT_{t-1}$ as well as Org_{t-1}, are included.

$$D\_S\_HEmp = \beta_{H1}\ D\_Turn + \beta_{H2}\ D\_Cap + \beta_{H3}\ D\_R\_HWage + \beta_{H4}\ D\_Exp + \beta_{H5}\ InvICT_{t-1} + \beta_{H6}\ Org_{t-1} + \beta_{L7}\ Years + \varepsilon_{Hi}$$
$$D\_S\_LEmp = \beta_{L1}\ D\_Turn + \beta_{L2}\ D\_Cap + \beta_{L3}\ D\_R\_LWage + \beta_{L4}\ D\_Exp + \beta_{L5}\ InvICT_{t-1} + \beta_{L6}\ Org_{t-1} + \beta_{L7}\ Years + \varepsilon_{Hi} \quad (11)$$

Again, SBTC, as stated in the first hypothesis, occurs if the coefficients β_{H5} and β_{L5} differ depending on the skill group. In the case of β_{H5}>0 and β_{L5}<0 or β_{H5}>0 and β_{L5}<0, technological changes are biased in the direction of high-skilled employees. The second hypothesis refers to the variable *Org*. In the case of β_{H6}>0 and β_{L6}<0, organizational changes are biased in the direction of high-skilled employees. The third hypothesis can be confirmed if β_{L2}<0. In that case, low-skilled employees and capital act like substitutes. If β_{H2}>0, high-skilled employees and capital are complements.

Equation (11) is calculated in three different models. First, only the variable *InvICT* is integrated in (11)a in order to test the hypothesis of SBTC. Second, organizational changes are considered as a cause for a changed skill demand, using the variable *Org* in (11)b. Third, a connection of both effects is analyzed. In this case, both variables *InvICT* and *Org* are included in the regression model (11)c. The dependent and explanatory variables with contents are listed in Table 5.5 in the appendix.

5.7 Results

The regression results of all models (11)a to 11(c) for manufacturing sectors are listed in Table 5.2. The highest coefficients can be found in the wage ratios. In contrast, the variable *D_Exp* is not significantly correlated with *D_S_HEmp* or *D_S_LEmp.* Considering SBTC in (11)a, the variable *InvICT* shows a positive coefficient for high-skilled and a negative coefficient for low-skilled employees. Therefore, technological changes are significantly biased towards high-skilled employees in manufacturing sectors and the first hypothesis of SBTC can be confirmed. Following the results of (11)b, the evidence of SBOC can also be confirmed for manufacturing sectors. The relationship between Org_{t-1} and *D_S_HEmp* is significantly positive, while Org_{t-1} and *D_S_Lemp* are negatively associated. The results of (11)c show that organizational changes can even explain more of the changes than technological changes.

Table 5.2: Results of the SUR-estimation for manufacturing sectors.

	(11)a		(11)b		(11)c	
	D_S_HEmp	*D_S_LEmp*	*D_S_HEmp*	*D_S_LEmp*	*D_S_HEmp*	*D_S_LEmp*
D_R_HWage	-0.050 (0.007) ***		-0.048 (0.007) ***		-0.051 (0.007) ***	
D_R_LWage		-0.048 (0.006) ***		-0.045 (0.006) ***		-0.049 (0.006) ***
D_Turn	-0.005 (0.006)	-0.005 (0.005)	-0.005 (0.006)	-0.005 (0.005)	-0.006 (0.006)	-0.005 (0.005)
D_Cap	0.002 (0.002)	-0.001 (0.002)	0.001 (0.002)	$-3.7e^{-04}$ ($1.5e^{-03}$)	0.002 (0.002)	$-4.6e^{-04}$ ($1.5e^{-03}$)
D_Exp	$-3.7e^{-05}$ ($1.6e^{-04}$)	$-3.1e^{-05}$ ($1.3e^{-04}$)	$-3.7e^{-05}$ ($1.7e^{-04}$)	$-7.5e^{-05}$ ($1.3e^{-04}$)	$-4.0e^{-05}$ ($1.6e^{-04}$)	$-2.9e^{-05}$ ($1.3e^{-04}$)
$InvICT_{t-1}$	0.012 (0.006) **	-0.012 (0.005) ***			0.007 (0.006)	-0.009 (0.005) *
Org_{t-1}			0.019 (0.004) ***	-0.013 (0.003) ***	0.018 (0.004) ***	-0.011 (0.003) ***
Const	-0.036 (0.008) ***	0.043 (0.007) ***	-0.042 (0.008) ***	0.008 (0.006)	-0.012 (0.008)	0.012 (0.007) *
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	12796	12796	12888	12888	12620	12620
Pseudo-R^2	0.0073	0.0094	0.0084	0.0094	0.0095	0.0107
Chi^2	94.71***	121.56***	109.54***	122.15***	121.09***	136.6***
B-P test	5775.126***		5721.505***		5683.051***	

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %. B-P test indicates the Breusch-Pagan test results.
Source: LIAB, 1993-2008. Own calculations.

While the coefficients of *Org*$_{t-1}$ remain constant, the coefficients as well as the significance levels of *InvICT*$_{t-1}$ decrease significantly in (11)c. The third hypothesis, assuming a complementarity between highly educated employees and capital, cannot be confirmed for manufacturing sectors. The coefficient of the variable *D_Cap* is positive for *D_S_HEmp* in (11)a, (11)b and (11)c, but the results are not significant. The same is true for the relationship between capital and low-skilled employees as substitutes. The coefficient of *D_Cap* is consistently negative, but not significant.

The results for the service sectors are listed in Table 5.3. Similar to the results for manufacturing sectors, the wages have the highest coefficients, while exports cannot significantly explain the changes in the labor demand. Following the coefficients in 11(a), SBTC can be confirmed for services as well. *InvICT*$_{t-1}$ and *D_S_HEmp* are positively correlated, while the relationship between *InvICT*$_{t-1}$ and *D_S_LEmp* is significantly negative. Compared to manufacturing sectors, the coefficients of *InvICT*$_{t-1}$ are even higher and the incidence of SBTC is stronger in service sectors. In contrast, SBOC cannot be found in service sectors. The coefficients of *Org*$_{t-1}$ in (11)b are negative and not significant for high- and low-skilled employees. The incidence of SBTC in service sectors can also be confirmed after controlling for organizational changes. The coefficients of *InvICT*$_{t-1}$ even increase in (11)c, although the significance level decreases slightly. Hence, the first hypothesis can be confirmed, while the second hypothesis is disproved for services. However, the third hypothesis, assuming a complementarity between *D_Cap* and *D_S_HEmp*, can be confirmed in all models 11(a) to 11(c) for service sectors. The assumption that *D_Cap* and *D_S_LEmp* act as substitutes, in contrast, cannot be confirmed. The coefficient of *D_Cap* is negative, but not significant in (11)a to (11)c.

To compare the results of the SUR estimations with those of a separate OLS estimation, the Breusch-Pagan test is analyzed. Following the results in Table 5.2 and 5.3, the residuals from the two equations are not independent and the SUR approach is more efficient than OLS for both, manufacturing as well as service sectors.[14]

[14] A correlation matrix of the independent variables as well as additonal descriptive statistics can be found in Table 5.6 and 5.7.

Table 5.3: Results of the SUR-estimation for service sectors.

	(11)a						(11)b						(11)c					
	D_S_HEmp			*D_S_LEmp*			*D_S_HEmp*			*D_S_LEmp*			*D_S_HEmp*			*D_S_LEmp*		
D_R_HWage	-0.048	0.011	***				-0.041	0.011	***				-0.048	0.011	***			
D_R_LWage				-0.020	0.006	***				-0.018	0.006	***				-0.020	0.006	***
D_Turn	-0.026	0.011	**	0.011	0.006	*	-0.027	0.011	**	0.011	0.006	*	-0.027	0.011	**	0.011	0.006	*
D_Cap	0.008	0.004	**	-0.003	0.002		0.008	0.004	**	-0.003	0.002		0.008	0.004	**	-0.003	0.002	*
D_Exp	$4.4e^{-05}$	$4.4e^{-04}$		$-2.8e^{-04}$	$2.5e^{-04}$		$1.8e^{-04}$	$4.3e^{-04}$		$-3.0e^{-04}$	$2.5e^{-04}$		4.3e-^{05}	$4.4e^{-04}$		$-2.7e^{-04}$	$2.5e^{-04}$	**
InvICT$_{t-1}$	0.024	0.014	*	-0.016	0.008	**							0.026	0.014	*	-0.018	0.008	**
Org$_{t-1}$							-0.005	0.007		$-2.6e^{-04}$	$3.9e^{-03}$		-0.007	0.007		0.002	0.004	
Const	0.008	0.020		0.020	0.011	*	0.026	0.018		0.011	0.010		-0.013	0.022		0.005	0.012	
Year	Yes			Yes			Yes			Yes			Yes			Yes		
N	6997			6997			7113			6921			12620			12620		
Pseudo-R^2	0.0086			0.0108			0.0091			0.0089			0.0095			0.0107		
Chi^2	60.91***			76.44***			65.65***			62.28***			121.09***			136.6***		
B-P test	2299.567***						2258.768***						5683.051***					

Notes: Standard errors in brackets. Significance levels: ***/**/* 1 %/5 %/10 %. B-P test indicates the Breusch-Pagan test results.
Source: LIAB, 1993-2008. Own calculations.

5.8 Conclusions

The thesis of SBTC is discussed since years, assuming that the increased demand for high-skilled employees can be attributed to technological changes. Several empirical studies have already found evidence that prove the SBTC thesis. However, organizational changes as a cause of the changes in the skill demand have received much less attention.

Using data from establishments in Western Germany from 1993 to 2008, it turns out that the incidence of technological and organizational changes depends on the sectors. Considering manufacturing sectors, SBTC can be found, but SBOC can explain more of the changes in the skill demand than technological changes. Moreover, the coefficients of technological change are not consistently significant anymore after controlling for organizational changes, proving that organizational changes provide a significant explanation for the skill-bias. Therefore, the first and the second hypothesis can be confirmed.

In contrast, SBTC is more present in service sectors, while SBOC cannot be found. In addition, capital and high-skilled employees act like complements in service sectors. Hence, the first and the third hypothesis can be confirmed for service sectors.

The results provide evidence of a skill-bias in Germany, where the bias can be attributed to technological changes in service sectors and rather to organizational changes in manufacturing sectors. However, the wage-ratios provide the strongest explanation for the changed skill-structure in the total employment. In any way, the results demonstrate the necessity to expand the skills on the German labor market, underlined by the topic of skills shortage, which has already been discussed years (Dychtwald et al., 2006). In addition, implications on company-level with regard to internal training measurements can be derived. Future research might focus on exactly those measures and their effectiveness in order to face the increasing demand for skills. In addition, besides the analysis of the changing employment shares in the total employment or in the wage bill between the individual skill groups, differences such as wage-inequalities within these groups have so far received less attention (Blanchflower and Slaughter, 1999: 68).

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Appendix

Table 5.4: Example of the Tobit wage calculation from 2000.

	Western Germany					
	low-skilled			high-skilled		
Age	1.148	(0.003)	***	0.596	(0.004)	***
Female	-19.960	(0.069)	***	-13.735	(0.129)	***
Nation	-0.369	(0.005)	***	-0.232	(0.007)	***
Hours	-2.915	(0.012)	***	-1.113	(0.026)	***
Const	54.202	(0.132)	***	86.796	(0.214)	***
N	1146236			543048		
Censored	96			195		
Chi^2	332104.51***			44775.31***		
Pseudo-R^2	0.0285			0.0084		
L-Likelihood	-5662875.4			-2648440.8		

Notes: Employee's age, sex, nationality and working hours as explanatory variables.
Source: LIAB, 1993-2008. Own calculations.

Table 5.5: Description of included variables in the regression equations.

Variables	Description	Coding	(11)a	(11)b	(11)c
D_S_HEmp	Changes in the share of high-skilled employees in total employment	Continuous	x	x	x
D_S_LEmp	Changes in the share of low-skilled employees in total employment	Continuous	x	x	x
D_Cap	Changes in the logarithm of capital measured by investments	Continuous	x	x	x
D_Turn	Changes in the logarithm of annual turnover of the previous year	Continuous	x	x	x
D_R_HWage	Changes in the logged wage ratio of high- and low-skilled employees	Continuous	x	x	x
D_R_LWage	Changes in the logged wage ratio of low- and high-skilled employees	Continuous	x	x	x
D_Exp	Changes in the share of exports in turnover				
$InvICT_{t-1}$	Investments in ICT within the last year	Binary	x		x
Org_{t-1}	Organizational changes within the last year	Binary		x	x
Year	Years	Binary	x	x	x

Table 5.6: Correlations of the independent variables.

	D_R_HWage	*D_R_LWage*	*D_Turn*	*D_Cap*	*D_Expt*	*Inv_ICT*$_{t-1}$	*Org*$_{t-1}$
D_R_HWage	1						
D_R_LWage	-1.0000	1					
D_Turn	0.0172	-0.0172	1				
D_Cap	0.0054	-0.0056	0.0815	1			
D_Expt	0.0028	-0.0030	0.0356	0.0148	1		
Inv_ICT$_{t-1}$	0.0094	-0.0107	0.0187	0.0262	0.0066	1	
Org$_{t-1}$	0.0111	-0.0112	0.0255	0.0105	0.0145	0.1975	1

Source: LIAB, 1993-2008. Own calculations.

Table 5.7: Mean and standard deviation of the dependent and independent variables.

Variable		N	Mean	Std. Dev.
Share$_t$				
	S_HEmp	61510	-1.0109	0.8762
	S_LEmp	73020	-0.5813	0.5811
	D_R_HWage	58729	0.2206	0.4192
	D_R_LWage	58729	-0.2473	0.4236
	Turn	69509	14.7978	2.3002
	Cap	39844	12.2716	2.5771
	Exp	72751	7.8142	18.5523
Difference$_{t\text{-}t\text{-}1}$				
	D_S_HEmp	41618	0.0007	0.2585
	D_S_LEmp	49651	0.0062	0.2126
	D_R_HWage	39570	-0.0017	0.2830
	D_R_LWage	39570	0.0002	0.2780
	D_Turn	48508	0.0107	0.3521
	D_Cap	26473	-0.0820	0.9372
	D_Exp	49496	0.1943	8.5655

Source: LIAB, 1993-2008. Own calculations.